Essays on the Analysis of Electricity Markets and Policy: Renewable Electricity and Demand Response

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Dedication

This dissertation is dedicated to my grandmother, my parents, my sister and my husband…

Zahide Boynuegri, Filiz Eryilmaz, Adil Eryilmaz, Tuba Eryilmaz and Emrah Ekici

Abstract

This dissertation focuses on renewable energy policy in the US and demand-side management in US regional electricity markets. Considering the existing state and the federal policies that promote renewable electricity generation, the analyses in this dissertation seek to explain the impact of those policies on investment in renewable energy technologies as well as the impact of more renewable generation on the markets and electricity consumers' behavior. This dissertation consists of three essays employing optimization and empirical analysis techniques to examine the relationships among renewable electricity generation, electricity demand and policy.

The first essay in this dissertation provides an understanding of the impact of uncertainties about renewable energy policy on wind energy investments. It considers the uncertainty about future state and federal policies that subsidize wind projects and how this uncertainty affects decisions to invest in wind energy. A real-options theory is employed to model the investment decisions of a firm to understand how irreversible investment in wind energy depends on federal subsidy uncertainties (the Production Tax Credit, or PTC) and price uncertainty in renewable energy markets. Results contribute to our understanding of the impact of the federal and state policy decisions on the profitability threshold to commit to a renewable energy investment. One of the major findings is that the uncertainty about the federal PTC policy lowers the profitability threshold to invest in wind energy and stimulates wind installations. The PTC incentive matters to investors in wind projects, and permanently removing the federal PTC policy may reduce future investment projects in the US. On the other hand, more stringent state RPS policies that would increase the demand for Renewable Electricity Credits (RECs) would tend to encourage wind investment.

The second essay examines consumers' response to electricity price changes in the retail and wholesale markets in the Midcontinent Independent System Operator (MISO) and it provides

a comparison between the retail electricity market, in which industrial consumers do not observe real-time price changes and pay a pre-determined flat rate, and the wholesale electricity market, in which consumers are able to change their electricity consumption based on real-time price changes. I estimate the demand for electricity by industrial customers using a two-stage model. Results show that industrial price elasticities in retail markets vary across states in the Midwest. Price elasticity estimates show that consumers in the wholesale market are less responsive to price changes than are consumers in the retail market.

The third essay provides an assessment of residential solar PV penetration and its implications for future electricity demand in the US. More specifically, this essay addresses the question of how rooftop solar penetration affects the residential electricity demand and how residential PV penetration affects electricity sales. Further, it examines the impact of the state policies (i.e., state Net Energy Metering policy, state regulatory status) on residential PV capacity additions. Results of the empirical analysis show that state policies promote adoption of rooftop solar in the residential sector. This causes a significant reduction in residential electricity demand from electric utility companies. Ultimately, results show that residential customers become more responsive to price changes with more solar electricity generation. States with higher scores for their encouragement of solar energy will see more dramatic reductions in utility sales to residential consumers.

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1. Introduction

The United States electric power sector has a sophisticated infrastructure that has been going through an important transition over the past two decades. This transition includes considerable growth in the integration of renewable technologies into the electric power system and improvements in the adoption of the energy efficiency and load management technologies. Total renewable electricity generation has increased by 40% between 2008 and 2013, installed renewable capacity has approximately doubled and the share of the total renewable electricity production in the US became approximately 11% of the total generation portfolio in 2013 (NREL 2013). On the electricity consumption side, electricity consumers have become smarter in consuming electricity. Large consumers have increased their investments in load management technologies and they are more able to participate in demand response programs. They can both reduce their consumption of electricity and shift consumption to off-peak times of the day. Residential customers have increased the number of distributed generation sources (e.g., consumer-owned rooftop solar). Overall, the growth in demand for electricity has declined over the past two decades (EIA, 2014).

Rules governing electricity generation and distribution are as complex as the infrastructure and are governed by federal, state and local entities. State and federal policies have changed dramatically in recent years, and these changes have played and important in changing the market structure and the economics of electric power in the United States. As one example, participants in the electricity generation side of the market have become more motivated to invest in cleaner and more efficient energy technologies with the support of federal and state incentives for renewable energy and energy efficiency.

This dissertation considers four leading policies that have influenced this transition of the US power markets: (1) the federal Production Tax Credits (PTC) policy, (2) the state Renewable

Portfolio Standards and the associated Renewable Electricity Credits market for wind; (3) the state Net Energy Metering Policy for solar and (4) retail competition for the implementation of demand response. Considering these policies and regulations, the essays in this dissertation aim to address research questions related to renewable electricity generation and electricity demand management in specific sectors and specific electricity regions in the US. This dissertation focuses specifically on electricity generation from wind and solar because renewable electricity generation from commercial wind and residential solar have shown substantial growth in the past decade. These renewable resources have benefited the most from the federal and state policies and economic incentives. In the consideration of demand response programs, the focus is particularly on industrial customers as large electricity users because large electricity users play an important role in the demand response programs of the Midcontinent Independent System Operator (MISO) region.

1.1 Dissertation Objectives

The goal of this dissertation is to provide an understanding of selected relationships between the economics of clean energy and policy. This dissertation also aims to provide a better understanding of the implementation of demand response resources in retail and wholesale markets of the Midwest region.

The first chapter provides an economic analysis of the investment decision in renewable energy, wind in particular, using a real-options framework. It provides an understanding of the impact of uncertainty about the renewable energy policy on this investment decision by finding a profitability threshold for investment. This chapter focuses explicitly on the uncertainty about the federal Production Tax Credits (PTC) policy and future Renewable Electricity Credits (RECs) market prices. The chapter develops and analyzes a model of a potential wind turbine investor's decision to invest in the face of such policy uncertainties.

The second chapter looks at the demand side of the electricity market and investigates whether industrial customers in the MISO region could serve as a demand response resource through utility-monitored dynamic pricing programs in MISO electricity markets. It considers whether regional retail competition, allowing customers to choose the lowest rate offering electricity provider, is likely to influence the adoption of demand response. This chapter provides an econometric analysis of the responsiveness of the industrial customers to the electricity price changes and the variation in this price-responsiveness across the states of MISO retail electricity market. Further, the empirical analysis in this chapter quantifies the MISO market response to the real-time price changes.

The third chapter provides an empirical analysis of the residential electricity demand considering the increasing distributed solar generation capacity in the United States. The focus of this chapter is the impacts of this increased distributed generation on utilities. While estimating the residential demand, the analysis in this chapter also quantifies customer responsiveness to electricity price changes with more residential rooftop solar installations.

The essays in this dissertation will contribute to the understanding of the economics of clean energy generation, markets and policy through the following research questions.

- How does uncertainty about the continuation of the Production Tax Credit subsidy and REC prices affect the decision to invest in wind energy?
- How do these sources of policy uncertainty interact and affect the investment threshold for wind energy in regional REC markets?
- How do consumers respond to electricity price changes in retail and wholesale markets in the MISO footprint?
- How does price-responsiveness change with the increasing capacity installations of distributed generation technologies?
- What is the impact of retail competition on demand response adoption?
- Does retail customer price-responsiveness have similarities with wholesale customer price-responsiveness?

Chapter 1

Uncertainty in Renewable Energy Policy in the United States and Decision on Investment in Wind

1.1 Introduction

Renewable energy resources have significant potential to supply energy, support energy security goals, and contribute to less carbon-intensive energy production. The United States, one of the largest electricity consumers in the world (EIA, 2012), has been successful in increasing the share of electricity produced from renewable sources. Electricity generation from non-hydro renewable resources is projected to grow by 3.7% in 2014, and wind is expected to contribute about 5% of total electricity generation in 2015 (EIA, 2014). In 2012, the largest share of US electricity generation capacity additions was coming from wind (EIA, 2012). This significant increase in renewable energy investments can be attributed, in part, to supportive government policies at both state and federal levels (Martinot et al., 2005).

Despite supportive federal and state policies, electricity production from renewables is still only a small fraction of the total energy supply in the United States. There are several possible reasons. First, renewable energy may simply not be cost-competitive with energy from non-renewable sources given current technology and prices. Even when renewable energy is economically feasible, it takes time to develop the underlying infrastructure. Second, uncertainties about future prices and technology may dampen current investments even though investment in renewable resources would be wise if current prices and technology were sure to persist into the future. Third, if most of the incentives to invest in renewable energy come from government policy, investors may be concerned that these incentives may not last. This essay focuses on the third reason and asks how uncertainty in renewable energy policy affects investment decisions in the United States.

Wind has been the renewable energy resource that has benefited the most from state and federal policies (Wiser et al., 2007); wind capacity has been the fastest growing renewable energy source in the US (EIA, 2012). National cumulative wind energy capacity has significantly increased (from 894 MW to more than 60,000 MW) between 1992 and 2013 (Lou, 2011; EIA, 2012, Brown, 2012; AWEA, 2013). In addition to the wind resource availability and spatial cost-effectiveness of renewable energy generation (Green Power Network 2013), investment in wind energy is also attractive when state and federal policies incentivize the investors who bear the considerable irreversible investment costs.

The federal government has promoted renewable energy through Production Tax Credits (PTC) since the passage of the Energy Policy Act in 1992. These credits are tax benefits received for production of renewable energy from biomass, wind, hydro, geothermal or solid waste. For example, investment in wind power is currently subsidized at $23 per megawatt-hour during the first ten years of a new renewable energy facility's operation, which covers almost one-third of the initial installation cost (Brown, 2012). Congress has repeatedly renewed these credits each time they were set to expire. Most recently, the PTC was set to expire on December 2013 and projects that were installed before January 1, 2014 continue to receive these credits. However, it is still unclear whether the PTC incentive will be available for future wind projects (Barradale, 2010; Brown, 2012). Wind developers are concerned that the permanent expiration of the PTC will have a significant impact on the industry, jobs and economic output from wind (Lantz et al., 2014). Thus, the impact of the uncertainty about the PTC incentive on future investment decisions in wind energy is unclear. Figure 1.1 shows the cumulative and quarterly increase in wind capacity installations between 2008 and the first quarter of 2014. Although the cumulative wind capacity installations have substantially increased since the first quarter of 2008, several on-and-off periods in the PTC policy created volatility in the quarterly capacity installations. Especially during the times when the federal government allowed PTCs to expire or when they were late in extending the PTC policy, capacity installations were approximately 70-92% lower nationally. Figure 1 clearly shows the significant drop in the capacity installation in the first quarter of 2013 after the federal government allowed the PTC to expire at the end of the last quarter of 2012. A study by Barradale (2010) also confirms that wind investments were considerably lower during the period of uncertainty about the future of the PTC incentive. Further, the EIA reported that approximately 40% of the wind capacity installations became available just before the expiration of the PTC in the last quarter of 2012 (EIA, 2012).

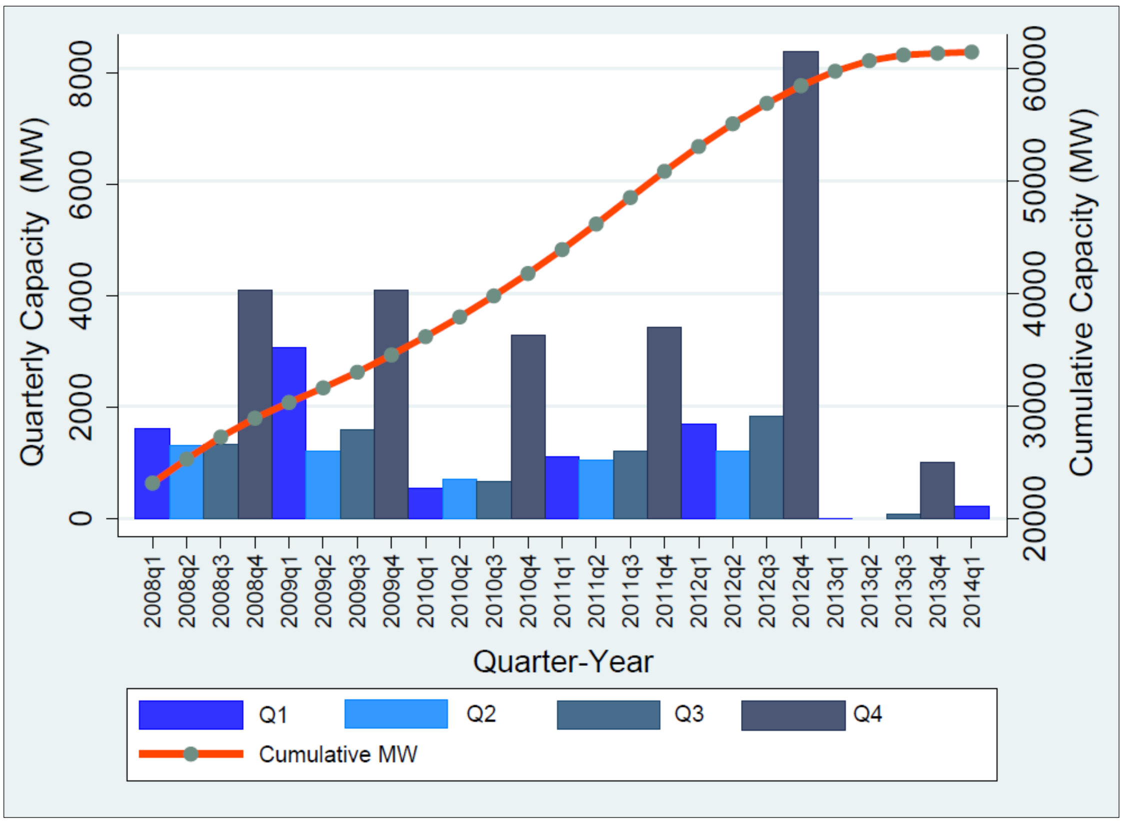

Figure 1. 1: Wind Capacity Installations between 2008 and 2014

Individual states have instituted Renewable Portfolio Standards (RPS) programs in which a certain fraction of total electricity must be produced using renewable sources. Applications of Renewable Portfolio Standards vary from state to state depending on the policy objectives such as reducing carbon emissions, promoting new investment in renewable energy, creating green jobs or innovating cleaner technology (Heeter et al., 2011). Renewable Portfolio Standard programs are implemented with Renewable Electricity Credits (RECs), tradable commodities used to facilitate compliance with the renewable energy requirements provided by the RPS. RECs are earned by producing electricity from renewable sources as an attribute of the generated renewable electricity, and excess credits can be sold to firms that fall short in meeting RPS requirements. RECs have been one of the fundamental drivers of successful private wind projects and have provided additional revenue for the producers (Cory et al. 2008).

REC prices are determined in regional trading markets and, usually, 1 REC is equivalent to 1MWh of electricity generated from wind. Based on the differences in the resource availability (e.g., wind speed) and the compliance market requirements, REC prices may differ by region (Cory et al., 2008; US DOE, 2013). Voluntary markets allow trading in green energy within and across the states that do not have RPS or that have already reached RPS goals (Heeter and Bird, 2011). Both the compliance and voluntary markets for RECs foster development of wind projects and provide additional revenue for these projects (Brown, 2012).

While state and federal policies continue to incentivize wind projects, a recent wind market assessment by the U.S. Department of Energy shows that relying only on current state Renewable Portfolio Standards (RPS) will not be sufficient to meet future wind development targets (Lu et al., 2011; Wiser et al., 2012). They find that supplementing the states' RPS programs with a federal PTC program supports increased wind investments. On the other hand, another market assessment by Dismukes (2012) argues that the PTC policy is inefficient, creating negative prices for wind, and that current state RPS requirement are sufficient to meet renewable energy targets. Therefore, future of the PTC policy is a contemporary debate in Congress as well as among researchers (Barradale, 2010).

I use real options theory (Arrow and Fischer, 1974; Pindyck, 1980, 1984, 1988, 2000, Dixit and Pindyck, 1993), which focuses on problems related to investment when the decision to invest is irreversible, to model the wind power investment decision under policy uncertainty. A few recent studies used this framework to examine investments in renewable energy considering various sources of market and policy uncertainty: uncertainty in future carbon prices and climate policy (Fuss, 2008, 2012), future fuel prices (Fuss et al., 2010; Lou, 2011), future pollution costs and pollution stock (Balikcioglu and Fackler, 2011), and future renewable and non-renewable resource stocks (Mosino, 2012). A recent study by Reuter et al. (2012) looked at investment decisions in wind energy under uncertain climate policy in Germany using real-options framework. Their findings showed that the policy and market uncertainties make higher level of incentives necessary for energy companies to commit to an irreversible investment such as wind (Reuter et al. 2012). In this essay, I build upon this theoretical framework and previous work to investigate the impact of uncertainty about federal renewable energy policy and stochastic Renewable Electricity Credits (REC) prices on renewable energy investment decisions. Research questions include: (1) how does uncertainty about the continuation of the Production Tax Credit subsidy affect the decision to invest in wind energy; (2) how do uncertain REC prices affect the decision to invest in wind energy; and (3) how do these two sources of uncertainty interact and affect investment threshold in wind energy in regional REC markets? This essay studies the uncertainty around the two important renewable energy policies that drive wind investments in the US and contributes to an understanding of wind investment thresholds of private power generating companies given uncertainty about future renewable energy policy. It provides an understanding of how these policy incentives influence the investment profitability threshold in different REC trading regions, where the REC market volatility and average prices vary.

1.2 Methods

I model the decision to invest in renewable electricity using a discrete-choice dynamic optimization problem. The decision to invest in renewable electricity production from wind energy is considered to be irreversible. I assume that the representative investor is a price taker and that the capacity of the wind turbine model is not large enough to affect electricity or REC prices. The investor knows the current REC and electricity price and knows that the RPS goals need to be met by 2034 (Wiser et al., 2012). I assume that the investor faces fluctuating REC prices and electricity prices could be high, average or low[1]. I assume two policy uncertainties in the model: (1) annual prices of Renewable Electricity Credits (RECs) follow a stochastic process, and (2) the federal government may or may not choose to continue the PTC incentive when it expires at the end of each year. I solve the model over a 20-year time horizon ($\mathrm{T} = 20$) because I expect that the renewable energy goals will be met by 2034. I assume that expected REC prices will settle into their long-term average values by the end of the time horizon because states will meet their RPS requirements and the supply of wind energy will be stabilized. Also, the Power Purchase Agreements (PPA) for private wind projects usually last for 20 years (Cory et al., 2008). Finally, the representative investor sells RECs for each unit of renewable energy produced from wind and it is assumed that 1REC=1MWh.

1.2.1 Optimization Model Framework

In the model, the representative investor maximizes the expected profits from producing wind energy. In each period, the investor can take two possible actions: invest in the renewable electricity production ($x_t = 1$), or not ($x_t = 0$), preserving the option to invest in future periods. The investor starts with the state variable $s_t = 0$, where the investment has not yet taken place. If the investor decides to invest in renewable electricity at time t ($\mathrm{x_t} = 1$), he bears the sunk cost of

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[1] I include electricity prices as deterministic categorical (high, average, low) variable to improve the computational efficiency. In the future work, I will allow for more fluctuation in electricity prices.

investment(C^{SUNK}) at that time. If the Production Tax Credit is in place ($\alpha_t = 1$), the investor receives the federal subsidy (τ) for each unit of electricity generated (N) from the wind turbine every year ($PTC_t = \tau \cdot N$). Energy production starts one year after investment, and then the investor receives revenue from electricity production ($p^e \cdot N$ where p^e is the electricity price and N is the amount of electricity produced) and from RECs (R_t) sold in the market for Renewable Electricity Credits at price q_t. Because electric grid may not always be able to handle excess power, I assume a curtailment rate for both the electricity and the RECs generated from a single wind turbine and sold to the grid. Further, wind turbines usually do not operate at their full capacity due to the intermittent nature of wind. I assume a capacity factor to adjust for the efficiency of the wind turbine. The investor pays constant operating and maintenance costs annually (C).

I assume that the investor has only one irreversible option to invest: x_t and s_t cannot both take the value of 1 in the same time period. The optimization problem of the representative investor is thus formulated as follows:

$$\max_{x_t} E \sum_{t=0}^{T=20} \frac{1}{(1+r)^t} [\pi(x_t;\ s_t, q_t, p^e, \alpha_t)] \tag{1.1}$$

subject to

$$\pi(x_t;\ s_t, q_t, p^e, \alpha_t) = s_t. [(p^e \cdot N + q_t. R_t) \cdot \theta - C] + x_t[\alpha_t \cdot PTC_t - C^{SUNK}]$$

$$V_{T+1}(s_{T+1,} \alpha_{T+1}, p^e, q_{T+1}) = \frac{1}{(1+r)} s_{T+1}. \left((p^e * N + q_{T+1} * R_{T+1}) \cdot \theta - C\right)$$

$$s_{t+1} = s_t + x_t$$

$$q_{t+1} = f(q_t, \varepsilon_{t+1})$$

$$s_t + x_t \leq 1$$

$$x_t \in (0,1)$$

$$s_t \in (0,1)$$

$$\alpha_t \in (0,1)$$

The expected benefits from investment depend on expected REC prices, expected federal PTC incentive and the electricity price. The terminal value received at time T+1 ($V_{T+1}(s_{T+1}, \alpha_{T+1}, q_{T+1}, p^e)$) is the present value of the stream of revenues from RECs and electricity at the prices in place at time T+1. Optimal investment decisions can be derived by recursively solving Bellman's equation:

$$V_t(s_t, \alpha_t, q_t) = \max_{x_t}\left[\pi(x_t; s_t, \alpha_t, q_t, p^e) + \beta E\left(V_{t+1}(s_{t+1}, \alpha_{t+1}, q_{t+1}, p^e | x_t)\right)\right] \tag{1.2}$$

The investor chooses the optimal decision in a particular stage at each possible state by maximizing the value of the investment at any time of the horizon. I use the COMPECON toolbox solver by Miranda and Fackler (2002) to solve this optimization problem. I use data on prices, government policy, and engineering specifications to specify the parameters of the optimization model, as outlined below. An investment decision in such large and expensive projects requires a detailed feasibility analysis. Therefore, we use a year as the time step, assuming that the investor makes a decision to invest annually.

1.2.2 Model Parameters

I use several data sources to obtain model parameters. First, I base the analytical model on a land-based wind turbine from the National Renewable Energy Laboratory (NREL) as a reference wind turbine project[2]. The representative wind turbine has 1.5MW power capacity providing about 4,862MWh/year per turbine in energy, which is approximately equivalent to the annual electricity consumption of about 500 residential homes per year (NREL, 2011; DOE, 2013). The initial sunk cost of investment for this particular wind turbine is about $2.1 million/MW. Operating and maintenance costs (O&M) constitute about 25% of the initial investment cost or

[2] Reference wind turbine project is a national assessment projects the levelized cost of wind energy in the US (Tegen et al., 2013).

$52,500/year/turbine, and O&M for wind turbines are generally fixed over a year period (NREL 2011); O&M costs are assumed constant in the model. Annual energy produced from the wind turbine is calculated as the amount of energy produced from a 1.5MW capacity wind turbine adjusted by the annual capacity factor. We assume 5% curtailment and a 37% capacity factor. The annual discount factor is 8%, and there are 8760 hours in year. Table 1.1 summarizes the parameters used in the model.

Table 1. 1: Model Parameters, Notation and Data Sources

Parameter Name	Notation	Value	Data Sources
Wind Turbine Capacity (MW/year/turbine)	M	1.5	EIA 2012
Annual Energy Production (MWh/year/turbine)	N	4,862 $(\mathrm{M} * \mathrm{k} * 24)$	NREL 2011
Amount of RECs Generated	$\mathrm{R_t}$	4,862	DOE 2012
Curtailment Rate	Θ	0.05	Assumed
Sunk Cost of Wind Turbine ($/MW/turbine)	$\mathrm{C^{SUNK}}$	2,098,000	NREL 2011
Annual O&M Cost for Wind Turbine ($/MW/year/turbine)	C	52,500 (1.5*35,000)	NREL 2011
Federal PTC Incentive ($/MWh)	T	23	DSIRE 2012
Capacity Factor (%)	k	37%	NREL 2011
Probability of Keeping the PTC Policy	P	0.7	Wiser 2007, Lou 2011 and Brown 2012
Discount Factor	B	0.08	NREL 2011
Total Hours in a Year	h	8760 hrs.	24*365

1.2.3 Modeling Prices and Uncertain PTC Policy

1.2.3.1. Uncertainty in the Production Tax Credits (PTC) Policy

One of the stochastic components in the model is the federal PTC policy. Revenues from the PTC are included in the model at the time of investment. If the PTC policy is in place at the time the investor decides to install a wind turbine, the investor receives \$23MWh (τ) per unit of renewable energy production (N) for the next ten years of energy production. By investing at any time t when the PTC is in place ($\alpha_t = 1$), the investor locks in a stream of payments worth $PTC_t = \tau * N$ each year for 10 years. If the PTC policy is not in place ($\alpha_t = 0$) at the time the investor decides to invest, then he will not receive any payments at time t: $PTC_t = 0$. I keep track of the investment decision at each time step and make sure that the PTC incentive is paid for only next 10 years after the investment decision if the investor were eligible to receive these credits before the PTC is removed in the next period.

$$PTC_t = \begin{cases} \sum_i^{10} \frac{1}{(1+r)^{t+i}} (\tau \cdot N), & \alpha_t = 1 \\ 0, & \alpha_t = 0 \end{cases} \tag{1.3}$$

The investor knows whether or not the PTC policy will be continued or discontinued with some probability, and these probabilities are independent across time intervals. To date, the government has continued the PTC policy. However, the PTC policy has an expiration date, and, as discussed earlier, the decision to extend it has often been the subject of contentious debate in Congress. Continuation of the PTC policy is therefore introduced in the model as a binary random variable$\{\alpha_t\}_{t\geq 1}$. More specifically, the PTC for wind expired in 2000, 2002, 2004, and 2012, and 2013 (Wiser, 2007; Lou, 2011; Brown, 2012). With the exception of year 2013, the federal government extended these credits after expiration. Consistent with the legislative history of the federal government's decisions, I have assumed that the probability of the federal government continuing the PTC policy is higher than the probability of the federal government allowing the policy to lapse. Thus, the probability of the federal government maintaining the PTC policy is assumed to be 70% (p) in the next time period whereas the probability of the federal government removing the PTC policy is assumed to be 30% (1- p). I also test the sensitivity of the results to different probabilities on the continuation of the PTC in the Results section. If the federal government removes the PTC policy, I assume that there is no chance that the PTC policy can be enacted again. This assumption is based on the shortened historical effective duration of the PTC policy. Renewable market projections on the PTC policy show these credits phasing out from the renewable industry (Wiser, 2007; Sherman, 2013). Similarly, there are studies showing that the PTC is no longer a cost effective policy (Palmer et al., 2005; Fell et al., 2012).

$$\mathrm{Prob}(\alpha_{t+1}|\alpha_t) = \begin{cases} p & \text{if } \alpha_t = 1, \alpha_{t+1} = 1 \\ 1 - p & \text{if } \alpha_t = 1, \alpha_{t+1} = 0 \\ 1 & \text{if } \alpha_t = 0, \alpha_{t+1} = 0 \\ 0 & \text{if } \alpha_t = 0, \alpha_{t+1} = 1 \end{cases} \tag{1.4}$$

1.2.3.2 REC Prices

REC prices (q_t), follow a Markov process in the model; future REC prices are a function only of current prices and a stochastic error term. I assume a commonly used mean reverting process for REC prices:

$$q_t = \delta(\mu - q_{t-1}) + \sigma\varepsilon_t \tag{1.5}$$

where δ is the mean reversion rate, μ is the average REC price, σ is the constant volatility and ε_t is the normally distributed i.i.d. stochastic term. I estimate $q_t = a + bq_{t-1} + \varepsilon_t$ using Ordinary Least Squares (OLS), and calculate the parameters in Equation (1.5) (Dixit and Pindyck, 1993):

$$\delta = -\ln(a), \mu_i = \frac{b}{1-a}, \sigma = sd(\varepsilon)\frac{\sqrt{-2\ln(a)}}{\sqrt{(1-a)^2}}$$

This mean reverting process fits the historical REC price data[3]. Table 2 shows the parameter calculations for the mean reversion model based on the OLS estimation. I use these parameters to simulate many REC price paths and generate the transition probability matrix from these simulated price paths.

REC markets are structured regionally because states have different RPS requirements to meet and RECs are delivered to regional REC markets (Heeter and Bird, 2012). There are various factors that influence regional REC markets: availability of the renewable energy sources, demand for RECs, and stringency of the RPS policies (Heeter and Bird, 2012; Green Power Network, 2013). Therefore, I consider the location-specific characteristics of RECs as well, and simulate REC prices for two different REC trading regions in the country: NEPOOL and PJM[4], considering the differences in volatility, mean-reversion rate and long-term mean. In Figure 1.2, I present the daily historical REC prices for these regions between 2006 and 2014[5]. A visual inspection of the historical spot prices in Figure 2 shows that PJM ($8/MWh) has lower average prices compared to NEPOOL ($23/MWh). Also, REC prices in NEPOOL are more volatile compared to the PJM market. Figure 2 only includes compliance RECs. Solar RECs and voluntary RECs are excluded from the series in order to consider only the required RECs traded in the market. In Figure 1.3, I include a histogram of the simulated REC price paths after calibrating the estimated model parameters for the overall REC market statistics. Also, I present the parameters for the mean reverting REC price process for these two REC trading regions in Table 1.2.

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[3] OLS regression outputs for two different models and the OLS model fit are provided in the Appendix Table 1.1 and Figure 1.1.

[4] REC Market regions includes states:
NEPOOL: NH, ME, CT, VT
PJM: DE, IL, IN, KY, MY, MI, NJ, NC, OH, PA, TN, VI, DC

[5] The REC market data is obtained from Marex Spectron and it includes daily bid and offer for each REC (e.g., SRECs, Wind RECs). I present the mid-point value of the bid and offer values.

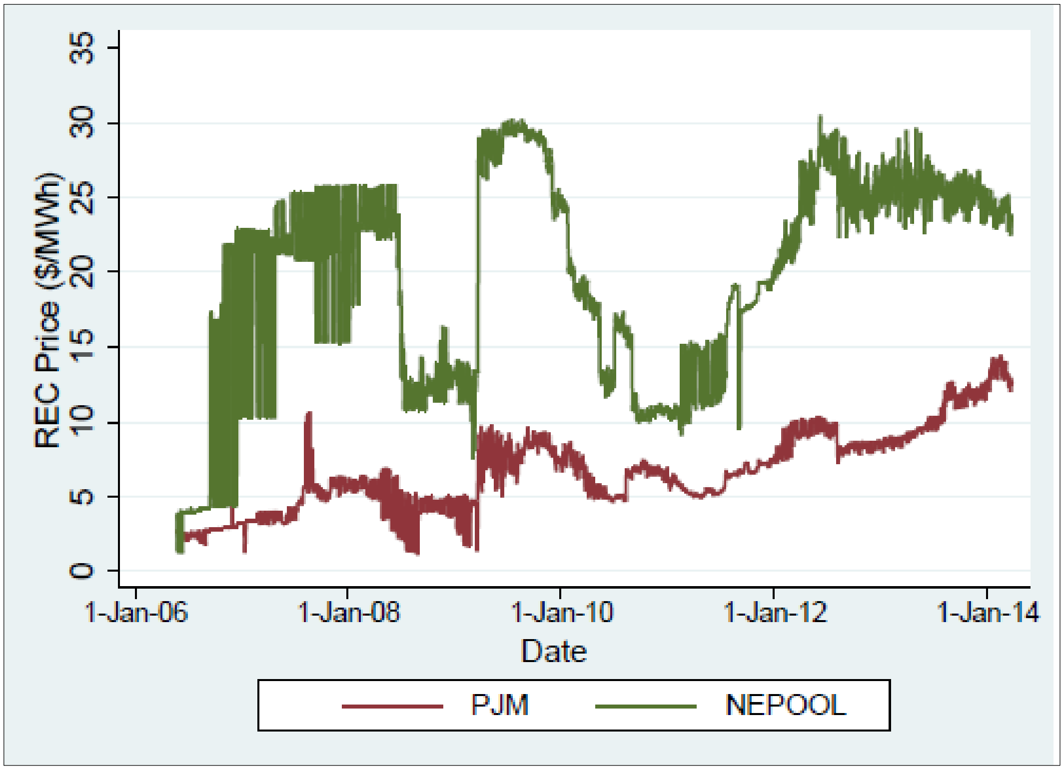

Figure 1. 2: Regional Historical Spot REC Prices in NEPOOL and PJM

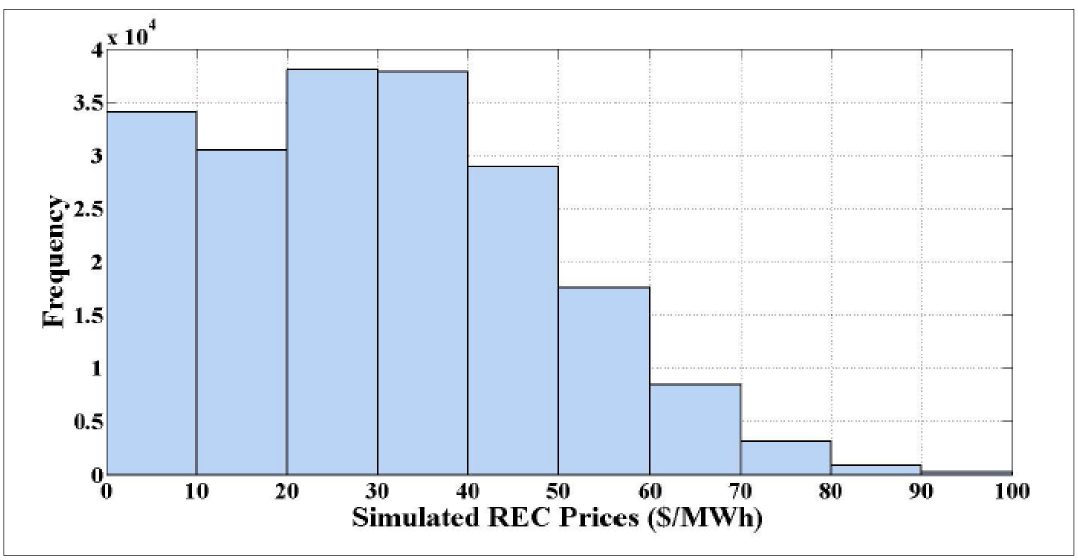

Figure 1. 3: Histogram for Simulated REC Price Paths

Table 1. 2: Parameter Calculations for Simulated REC Price Paths

Parameter	PJM	NEPOOL
Mean Reversion (δ)	0.5310	0.9784
Average Price (μ)	$7.4/MWh	$21.8/MWh
Constant Volatility (σ)	2.89	9.5

1.2.3.3 Electricity Prices

Electricity price statistics are similar for PJM and New England between 2006 and 2014, where the average electricity prices range between $60/MWh and $62/MWh both for PJM and NEPOOL. Similar to the REC market prices, the average electricity price is higher in the Northeast, where the monthly average electricity price reached up to $131/MWh between 2006 and 2014. I categorize the electricity prices as high (H), average (A) and low (L) based on the summary statistics in Table 1.3. For example, in PJM, the low electricity price is $33/MWh; the average electricity price is $60/MWh and the high electricity price range is $130/MWh. In New England, the low electricity price is $34/MWh; the average electricity price is $64/MWh and the high electricity price range is $131/MWh

Table 1. 3: Summary Statistics for Regional Electricity Prices

Parameter	Min	Mean	Max	Std.Dev
PJM ($/MWh)	33	60	130	19.09
New England $/MWh)	34	64	131	20.37

1.3 Results

The solution of this investment problem involves finding the REC price threshold that determines an investment decision. The decision to invest depends on whether REC prices reach the threshold for the given time period, whether the PTC policy is in force, and the level of the electricity price. The threshold for investment divides the space into two regions. Above the boundary is the price at which an investor will choose to invest; below this price, an investor will choose not to invest. Also, the investment threshold represents the critical minimum REC price that the investor will commit to the investment in wind turbine. The critical REC prices for investment are within the range of $15/MWh and $30/MWh with the PTC policy and within the range of $30MWh and $85/MWh without the PTC policy. Figure 1.4 shows the investment threshold with and without the PTC policy with *average* electricity prices.

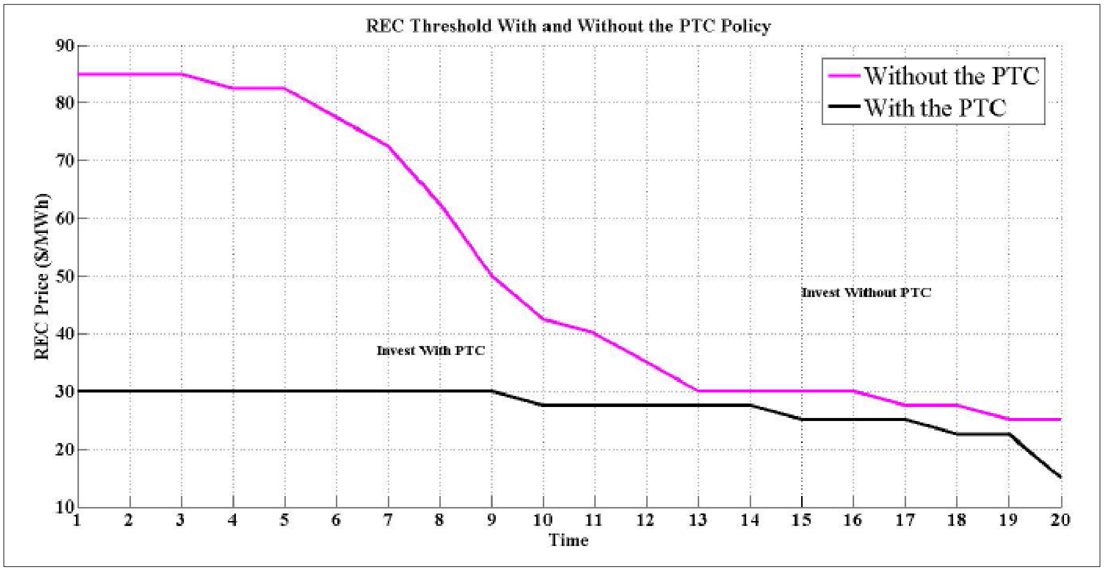

Figure 1. 4: REC Price Threshold with and without the PTC Policy

The REC price threshold depends on time and it decreases as the end of the horizon approaches. The level of decrease in the REC threshold over time depends on whether the PTC policy is in force or not and the volatility of REC prices. The investor requires a higher price earlier in the horizon because of the greater possibility of lower future prices (i.e., higher REC prices reverting to their mean) with uncertain REC prices. With the PTC policy, the investor requires lower REC prices to invest. Without the PTC policy, REC threshold is higher than the threshold with the PTC policy. The reason for this is that the investor receives the PTC, which covers about one-third of the initial investment cost; receiving these tax credits substantially lowers the cost of investment (Linn and Richardson, 2013). Moreover, the investment threshold also has a wider range when there is no PTC: the threshold starts from $85/MWh and drops to

$30/MWh. However, the investment threshold starts from $30/MWh and drops to $15/MWh when the investor receives the tax credits. This shows that the investor invests at higher REC prices in earlier time periods to recover the investment costs without the PTC policy but he would commit to the investment at lower REC prices towards the end of the horizon. The investor is willing to invest at lower REC prices as the end of the horizon approaches because there is no longer substantial uncertainty about REC prices dropping towards the end of the horizon.

We also find that, with high electricity prices, the investment threshold decreases. This suggests that higher electricity prices stimulate investments even when REC prices are low. Further, with higher electricity prices and with the PTC, we find that the minimum REC price for investment is the lowest compared to the other cases. Conversely, with lower electricity prices, we find higher minimum REC threshold for investment. In fact, consistent with the initial results, the threshold is higher when there is no PTC policy regardless of the level of electricity prices. Interestingly, the minimum investment threshold is considerably lower with high electricity prices even when there is no PTC policy. This suggests that the electricity prices may be the primary driver of wind investments without the PTC policy. In other words, the investor does not require as high REC prices to invest without the government subsidy if the electricity prices are sufficiently high. In Table 1.4, we provide the simulation results for low, average and high electricity prices considering the cases with and without the PTC policy.

Table 1. 4: REC Threshold at t=1

	Low	**Average**	**High**
With the PTC Policy	$32.5/MWh	$30/MWh	$25/MWh
Without the PTC Policy	$98/MWh	$85/MWh	$35/MWh

Finally, our results show that, with stochastic REC prices and the uncertain decision of the federal government about the PTC policy, the investor's decision to invest is affected by policy uncertainties. Because of the lack of information about the federal PTC policy and the possibility of volatile REC prices in the future, the investor has an incentive to invest before missing the chance to receive the PTC.

1.3.1 Regional REC Thresholds for Investment

Solutions in PJM and NEPOOL also show that the REC threshold is always lower with the PTC policy than it is without the PTC policy. However, investment decisions may vary across regions based on differences in REC market characteristics (e.g., volatility, average price, mean reversion parameter). Solving the investor’s problem for the two regions with the calibrated values, I find differences in the REC price threshold among the regional REC markets. Without the PTC policy, this wind project would not be built in PJM and NEPOOL at current REC and average electricity prices. However, with the PTC policy, the investor in PJM, where there is relatively lower average REC market price and more volatility, requires a higher critical REC price threshold. The simulations results for PJM and NEPOOL include average electricity prices. Table 1.5 provides the range for REC price thresholds for PJM and NEPOOL regions with and without the PTC policy.

Table 1. 5: Simulations for Different REC Trading Regions

Regions	PJM	NEPOOL
With the PTC	$0-$72	$0-$23
Without the PTC	Not invest	Not invest

1.3.2 Sensitivity Analysis

The analytical model is sensitive to the level of uncertainty about the government's decision on the PTC policy. In the initial simulations, I calibrated the probability of the government's decision to continue the PTC policy as 0.7 and the probability of the government's decision to remove the PTC policy as 0.3 (baseline scenario). With a higher probability ($p = 0.9$) of continuation of the PTC policy, the REC threshold increases. If the probability of keeping the PTC policy is higher, it is not as critical for an investor to invest now rather than later. The investor would be able to invest at higher REC prices to maximize his profits at any time with the higher possibility of receiving the tax credits. When, however, the PTC policy is to be continued with substantially lower probability ($p = 0.1$) than the baseline scenario ($p = 0.7$), the minimum investment threshold decreases. When there is higher probability of not receiving the tax credits if the investment is made in the future, the investor is willing to invest at lower REC prices in order to obtain the PTC.

I also perform a sensitivity analysis to identify the impact of changes in REC price parameters on the investment threshold. The model is sensitive to the mean reversion (δ) and constant volatility parameter (σ) of the stochastic REC price process. I compare the REC price thresholds with higher and lower values of these parameters. With higher mean reversion rate and higher volatility in the REC market, the investment threshold increases. Table 1.6 summarizes the direction of change of the critical REC price threshold for different values of the parameters.

Table 1. 6: Sensitivity Analysis: Direction of Change in REC Threshold

	Higher $\boldsymbol{\delta}$	**Higher $\boldsymbol{\sigma}$**
With the PTC	Increase	Increase
Without the PTC	Decrease	Increase

1.4 Discussion and Policy Implications

The purpose of this essay is to study the two important renewable energy policies in the US and to consider the effect of uncertainty on the investment threshold for a particular wind energy investment project. The findings of this analysis have important renewable energy policy implications. First, uncertainty about the future of state and federal renewable energy policy will influence investment decisions. In particular, uncertainty about the future PTC policy is critical for investment decisions in wind energy. The PTC policy is a substantial incentive for wind investment projects in the US, and uncertainty in the PTC policy's future will actually encourage current investment in wind. If there is a strong possibility that the PTC policy will expire, potential investors are prodded to take advantage of the policy while it is still in force. A large body of research supports that the federal PTC policy has an important role in making wind the top renewable resource to generate electricity in the US (Wiser et al., 2007; Lu et al., 2011). The wind manufacturing industry is concerned that the lack of a PTC would decrease the demand for wind installations and dampen economic output from wind deployment (Lantz et al., 2014). Another implicit effect of the future uncertainty in the PTC policy is that it may cause an accumulation of high wind generation capacity due to excess amount of wind investments before the federal policy expires. The practical implications of such stimulation of renewable energy earlier may not always be favorable. For example, wind technology may become more cost-efficient in the next 20 years and a large amount of the incentive may be wasting resources for an already advanced cost-efficient technology (Reuter et al., 2012; Dismukes, 2012).

In the absence of such a federal incentive in the future, state incentives will play a larger role for wind investment projects. Investors will require higher revenues from selling RECs in order to invest. REC market volatility will be a more important factor, as volatility tends to dampen the incentive to invest. Without the PTC policy, the incentive to invest in wind will depend on energy prices, REC prices, and REC price volatility. If there are more stringent state RPS policies in the future, it may increase the demand for RECs and ultimately increase REC prices and renewable energy suppliers' revenues.

Regional market differences may also have different implications on investment decisions in wind energy. If the regional REC market prices are considerably lower (e.g., PJM) or the market is more volatile (e.g., NEPOOL), the federal government's decision to remove the PTC policy may dampen investments in renewable energy. In addition to the state RPS and federal PTC policies, regional electricity prices may influence the investment decisions. In regions with higher electricity prices, the investors may have an incentive to invest even though REC prices are very low. Moreover, states and Independent System Operators (ISOs) continue to promote renewable energy development and integration with other policies (Wiser et al. 2012). For example, the Texas Competitive Renewable Energy Zone (CREZ) program by ERCOT is projected to include 18,500MW of wind power by 2013 by expanding the transmission lines (Potomac Economics, 2012; Wiser et al. 2012). This has caused an excessive supply of RECs in ERCOT, which has caused lower average and more stable REC prices (Heeter and Bird, 2012). RECs from wind generation capacity have increased with the CREZ project from 3135 MW (ERCOT, 2006) to 12,776 MW (ERCOT, 2012) between 2006 and 2012. The large amount of wind investments in a short time in ERCOT generated a large supply of wind energy and lower REC market prices, which did not provide as much incentive relative to the other regions (Center for Energy Economics, 2009). Therefore, the uniform structure of the PTC policy should be considered carefully. There are examples of restructuring the government renewable energy incentives in Europe, in the context of a feed-in tariff, which is a fixed tariff paid for each unit of electricity from renewables (Reuter et al., 2012). Researchers have shown that a non-linear feed-in-tariff could potentially save the government spending on the policy (Reuter et al., 2012). In addition, I assumed a particular technology in a particular location in this essay but market conditions, installment costs and wind resource availability varies across the country and the uniform structure of PTC may create policy inefficiencies and fairness issues (Dismukes, 2012). Further, although the PTC provides renewable investments a great source of financial incentive, the federal PTC policy is costly to the society's taxpayers compared to the state portfolio standards. Therefore, redesigning the PTC policy with variable rates based on the location, efficiency and capacity, and removing the uncertainties around the PTC policy would stimulate wind investments at the right time and in the right locations, where wind energy would actually contribute to the generation mix to provide cleaner electricity.

In this essay, I do not specifically model whether it is better to remove or continue the PTC but I show that uncertainty has implications on the investment decision on wind energy and I suggest that a permanent government decision on the PTC policy would eliminate one of the uncertainties for the investors in these projects although removing uncertainty may dampen the investments in short-term.

1.5 Conclusions

This essay solves the problem of modeling a representative investor's decisions to invest in renewable energy over a 20-year time horizon. A discrete choice optimization model is employed for a price-taking investor who must decide about investing in a 1.5 MW capacity wind turbine. The analytical model includes two sources of uncertainty: 1) uncertainty about the federal government's decision to maintain the Production Tax Credits (PTC) policy, and 2) uncertainty about the Renewable Electricity Credits (REC) prices. I solve the model using dynamic programming, and I provide a minimum REC price threshold for the investment decision, which depends on the PTC policy and REC prices and decreases as the end of the time horizon approaches. I find that the REC threshold is lower with the PTC policy. I also show that the investment decision is sensitive to the level of uncertainty about the PTC incentive and the REC prices. A higher likelihood of continuation of the PTC policy increases the REC price threshold for investment in wind energy. This chapter contributes to an understanding of how the uncertainties in these policies will impact future wind investments over the next 20 years.

As a concluding remark, solving this model for the U.S. wind industry would have important implications. An extension of this study would look at the impact of uncertainty in state and federal policy on wind energy investments in conjunction with the heterogeneity in wind turbines and employ empirical methods to demonstrate the impact of the uncertainty around the PTC on the historical investments in the US. Although the simulations are based on a particular land-based wind turbine and sensitive to the calibrated parameter values, the model framework is applicable to different types of wind turbines (i.e., different capacity and cost levels) and other renewable energy sources with high initial investment costs, such as solar energy.

Chapter 2

Price responsiveness in retail and wholesale markets: Implications for demand response in Midwest electricity markets

2.1 Introduction

While the wholesale price of electricity varies considerably across time of day and locations, electricity end-users usually pay a fixed retail-rate for their electricity. Relative to a situation in which end-users pay a retail price that tracks the wholesale price in real-time, paying a flat retail-rate ensures end-users consume more electricity during peak hours when electricity is expensive to produce, and consume less during off-peak hours when electricity is cheaper to produce (Faruqui et al. 2009; Faruqui 2010). Demand response initiatives (e.g., time of use pricing, critical peak pricing, real-time pricing, interruptible load control) offer consumers an opportunity to reduce expenditures on electricity by shifting or reducing their electricity consumption in response to real-time price changes. Demand response also helps to smooth peak electricity prices by shifting low-value energy consumption behaviors to a time when electricity prices are correspondingly low and similarly, engaging in only high-value energy consuming activities at times of higher energy prices (Chao 2008; Alcott, 2009; Alcott, 2011; Cooke 2011). Demand response programs have been adopted across different electricity markets and Independent System Operators across the US. In 2013, demand response programs have contributed to 9.2% reduction in national peak demand, where 47% of the national peak reduction has come from industrial customers (FERC 2014).

In traditionally regulated electricity markets, state public utilities commissions (PUCs) play an important role in regulating the electricity market, and state regulatory bodies determine rates. In a deregulated market, consumers can choose to purchase electricity from alternative retail electric suppliers and these suppliers can offer a variety of pricing mechanisms - making the market environment more competitive (Nazarian 2012). With the exception of Illinois, Ohio and Michigan, states in the Midcontinent Independent System Operator (MISO) system are traditionally regulated. However, regionally, in the MISO footprint, electricity supply has recently been restructured. Electricity prices are determined in the wholesale market, while electricity distribution services and distribution rates are regulated by the state. Further, the MISO market reduced its peak demand by approximately 10% through demand response in 2013 (FERC 2014). However, unlike the U.S. as a whole, large energy consuming industrial customers in the MISO market have not significantly contributed to actual peak demand reduction through dynamic pricing programs (Cappers et al. 2010).

Understanding consumers' abilities to respond to price changes is necessary in order to infer whether state-level retail markets with more price-responsive customers are associated with more price-responsive sub-regional wholesale markets during price-peaking hours. In addition, exploring industrial sector retail price responsiveness may also provide insights into where dynamic pricing programs might better access MISO's underutilized industrial demand response resources.

Papers in the demand response literature often show that demand response benefits customers as well as system reliability, but some questions remain (Loughran and Kulick 2004; DOE 2006). To what extent do consumers respond to price changes? What is the impact of state retail competition on demand response adoption of large industrial users? What is the relationship between state-influenced retail demand response and regional wholesale price responsiveness? As customers seek to reduce the cost of their electricity use and states seek to implement more demand response programs, improved understanding of price elasticities across regional wholesale electricity markets and different state-policy environments is critical to both the design and adoption of demand response (Cappers et al. 2010; Craig and Savage 2013).

In this essay, I estimate the industrial price elasticity of demand at the retail level and allow for the possibility of heterogeneity in price-responsiveness across states. Second, I estimate wholesale electricity demand in the MISO market, also accounting for heterogeneity across sub-regions. Then, I discuss the implications of industrial demand response on wholesale market price-responsiveness. In doing so, the study makes several contributions. First, it contributes to an understanding of how well price responsiveness on the part of retail industrial consumers is established in a deregulated state (e.g. Illinois) compared to in a regulated electricity state (e.g. Minnesota). Considering state-level industrial productivity and dynamic pricing adoption variation, this study analyzes industrial customers' response to price changes in the long-run (i.e. annually) in a market environment where these industrial customers are assumed to operate, largely, within monthly flat retail rate electricity contracts. While applications of demand response can be found in residential, commercial and industrial sectors, I focus on the industrial sector. This sector is a high energy-using sector where electricity consumption varies significantly among industrial processes and peak demand reduction in these large industrial customers can be substantial. Second, this chapter provides an estimate of the current price response in the MISO wholesale market, where the electricity price is determined on an hour-by-hour basis and where peak demand responds differently to the real-time price changes across sub-regional hubs within the system. Third, this chapter provides a discussion on the connection between industrial price responsiveness at the state level and the price responsiveness in the wholesale market with respect to state demand response performance over time. There is currently a demand response capacity in the retail market in MISO states; however, demand response has not yet been implemented to its full potential, especially in the context of industrial customers.

2.2 Background

2.2.1 Significance of Industrial Customers

In this study, I focus on industrial customers in the MISO states. Studying industrial customers for demand response is important for three reasons. First, they consume a large amount of energy, particularly in the MISO (EIA 2014). The share of industrial sales across the whole of the U.S. is 27% (EIA 2013) and 36% in the MISO. Second, large industrial customers are important to utilities because of the relatively high rates paid by industrial customers and large revenues generated by the segment. Utilities are thus open to offering alternative prices to sustain industrial customers such as block pricing (Spees and Lave 2007). A considerable portion of the demand response programs are offered to the industrial customers in MISO market (Bharvirkar et al. 2008). Third, industrial customers have strong incentives to increase load management and energy efficiency through state and federal programs (Borenstein, 2005; Energy Star 2014) and often have the technical capability to manage their electricity demand (e.g., smart meters, energy management units within a plant and industrial energy efficient technologies) (Gillingham et al. 2006). Ultimately, industrial customers in the Midwest constitute approximately 14,800MW of peak demand reduction capacity, where residential customers make up only 6,000MW of peak demand reduction capacity (Cappers et al. 2010). They are, therefore, a key resource in the wider implementation of demand response.

Studies have found that price elasticity can range between -0.2 and -0.7 for residential customers, and there is little evidence for elastic demand in either the residential or commercial sector (Bernstein and Griffin 2005; Bohi and Zimmerman 1984; Houthakker et al. 1974; Labandeira et al. 2010; Maddala et al. 1997). Bernstein and Griffin (2005) found significant differences in the residential and commercial price elasticity of demand for electricity among states and regions in the US. Most recently, Pielow et al. (2012) estimated industrial and commercial sector short-term and long-term price elasticity of demand in four different states

(Ohio, Michigan, Texas and Virginia) and found differences in the price of elasticity demand across regions. The few studies that considered electricity demand estimated the price elasticity of demand for industrial consumers to be between -0.14 and -0.6 (Elkhaifif 1992; Goldman et al. 2007).

Shwarz (2002), Patrick and Wolak (2001), Fan and Hyndman (2011) and Lijesen (2007) measured real-time elasticity. These studies found that the real-time price elasticity of electricity consumption is lower than the elasticity estimated with annual or monthly data. Their estimated real-time elasticity ranged between -0.04 and 0.43.With the exception of the Shwarz et al. (2002) study, these studies concluded that demand response to real-time price changes might not be very effective in reducing the quantity demanded due to the low price elasticity of demand (Lijesen 2007, Patrick and Wolak 2001). However, Shwarz et al. (2002) showed that depending on the customer category (e.g. industrial customers with interruptible production processes) and the time of day or a month in a year, quantity changes could be substantial. A small price elasticity rate did not necessarily indicate a small reduction in the industrial electricity demanded in real time (Shwarz et al. 2002).

2.2.2 Demand Response in the MISO

Utilities offer demand response programs to residential, commercial, and industrial customers in the MISO. The Energy Information Administration (EIA) collects data on utility demand response programs offered to end-use customers every year. In the retail market in 2013, including residential, commercial and industrial customers, there was on average 11,100MW of estimated capacity for peak demand reduction in the MISO footprint, where only 2,412MW of peak demand was actually reduced. North Dakota (6,482MW) and Indiana (763MW) have the highest potential (i.e. maximum peak demand reduction capacity) peak demand reduction capacity whereas Montana (0MW) and Missouri (13MW) have the lowest potential peak demand reduction capacity from demand response. However, states usually did not reach their maximum capacity of demand response. For example, in 2013, the actual peak demand reduction in Minnesota was only 43MW and in Wisconsin, it was only 22MW. North Dakota, with the highest potential peak demand reduction capacity, has actually reduced 11% of the potential peak demand reduction capacity.

In 2013, Minnesota and Wisconsin had the highest number of customers enrolled in dynamic pricing programs (3883 in Minnesota, 2538 in Wisconsin), whereas Montana had the lowest number of customers enrolled in dynamic pricing programs (90). The total cost of the incentives paid to the industrial customers by the utilities also varies across the states that participate in dynamic pricing programs. These incentives may include the cash rebates and reductions in tariffs for industrial customers in return to their participation in the dynamic pricing programs. Minnesota has the highest spending on the incentives for industrial customers to participate in any type of demand response program while Montana has the lowest amount of incentives paid to the industrial customers.

Figure 2.1 shows the total number of industrial customers enrolled in dynamic pricing programs and the total cost of the financial incentives paid for the industrial customers to participate in demand response programs in 2013. Figure 2.2 shows the potential capacity of peak demand reduction from *any* types of demand response programs including interruptible load and direct load control and the total number of customers with any other type of DR programs besides dynamic pricing in 2013.

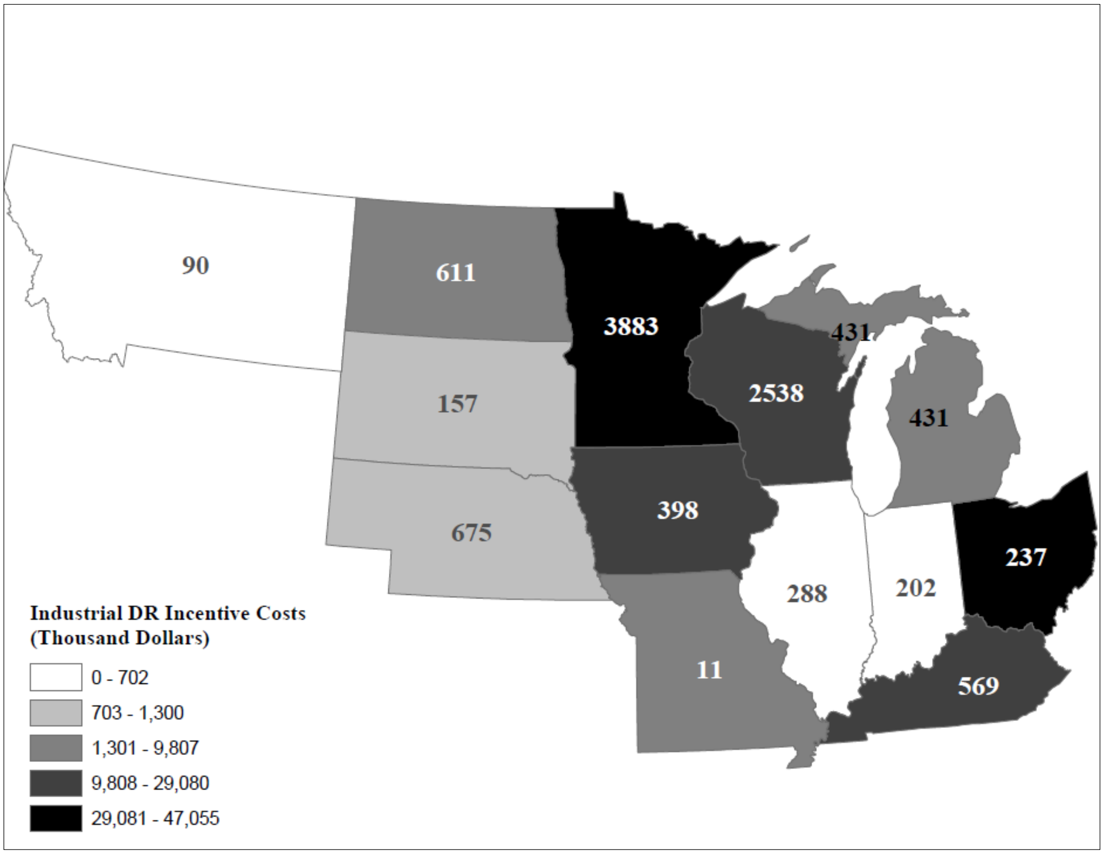

Figure 2. 1: Total Cost of the Incentives Paid to the Industrial Customers (Color-Coded) and Number of Industrial Customers (overlay values) with Dynamic Pricing Programs in 2013 (Source: Energy Information Administration, 2013)

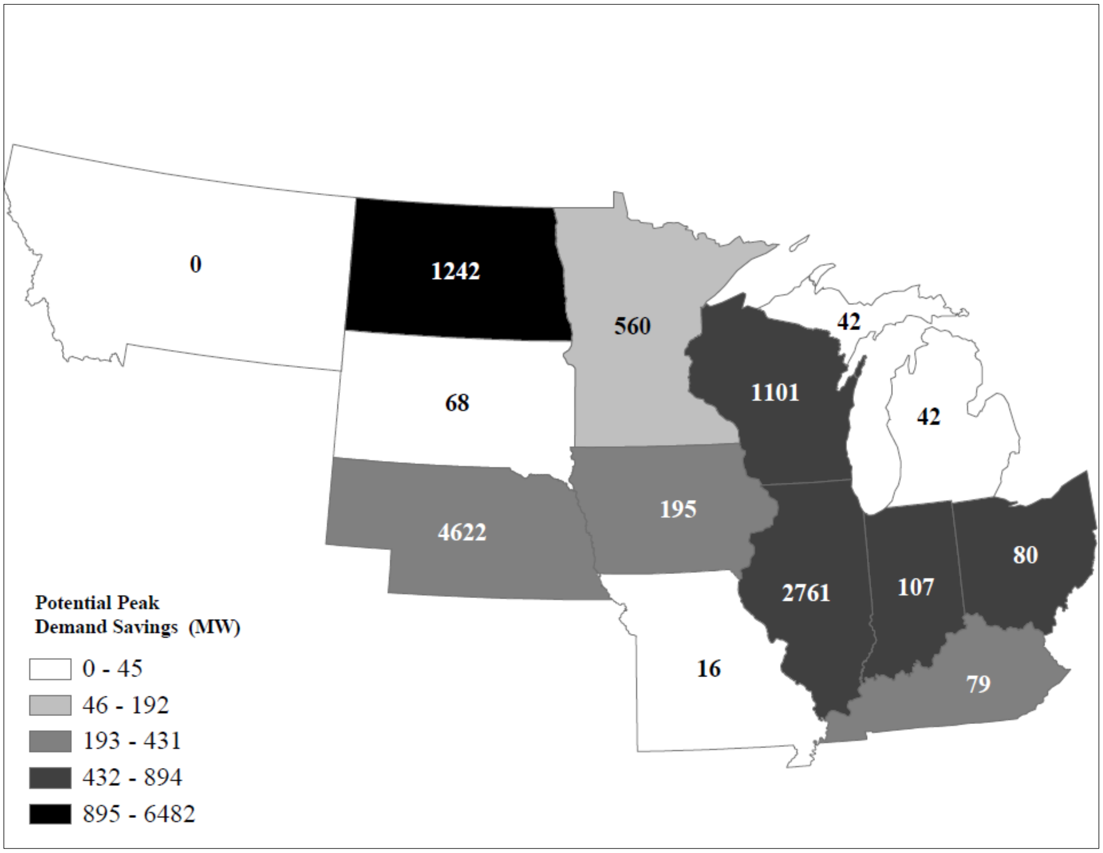

Figure 2. 2: Potential Peak Demand Savings (Color-coded) and Total Number of Industrial Customers (overlay values) with Any Type of Demand Response Programs in 2013

There are various types of demand response programs offered in the MISO (Earle et al. 2008; Heffner and Sedano 2008; Pfienberger and Hajos, 2011).

Incentive Based Programs

- **Direct Load Control (DLC):** Load serving entity contracts directly with the customer to reduce/curtail electricity use. For example, direct load control program participants are often paid $5 to $6 kW/month.
- **Interruptible Load (ILoad):** Electricity users agree to curtail a certain amount of electricity usage through a pre-defined agreement, and the customers may be subject to a penalty if they do not reduce their use under agreed conditions. For example, interruptible rate program participants are usually subsidized with $6kW/month payment.

Dynamic Pricing Programs

- **Time-of-Use (TOU):** The electricity customer is provided with different fixed rates among the on-peak and off-peak periods; however, the customer is not able to change the response dynamically.
- **Critical Peak Pricing (CPP):** The electricity customer is informed about the dynamic pricing of electricity production, and they reduce the electricity consumption during peak hours and reduce the electricity costs they incur. The customer receives calls from the load serving entity during peak hours, and the customer chooses to respond or not to respond to the peak prices.
- **Real-Time Pricing (RTP):** The electricity customer is informed about hourly prices and can decide to reduce consumption when prices are high. This DR resource provides customers with the most accurate electricity supply costs.

The type of dynamic pricing programs offered in the states also varies. All MISO states have Time-Of-Use prices as of 2013 but states that have high incentive payments for industrial customer to participate in demand response programs (e.g. Minnesota) or states that have high potential peak demand reduction capacity (e.g. North Dakota) do not have Real-Time Pricing programs. Real-Time Pricing programs are mostly offered in deregulated states (e.g., Illinois, Michigan, and Ohio) in the MISO region. I present the type of dynamic pricing programs that are offered in 2013 across MISO states in Appendix Table 2.1.

This table shows that the level of demand response adoption by the industrial customers varies at the aggregate state level and industrial customers in any type of demand response programs are not actually reducing their peak demand to its full potential in MISO states. This indicates that there are differences in these states with respect to the level of responding to the price changes. Therefore, quantifying the variation in price elasticity across the states is important for industrial demand response adoption in the MISO region.

2.3 Methods

2.3.1 Annual Retail Market Model

I estimate industrial and total electricity demand in the retail market of the MISO footprint using a fixed-effects estimation method. I assume a Cobb-Douglas functional form for industrial electricity demand. $E_{s,t}$ represents the quantity of electricity consumed, where subscript s represents states and t represents years. Industrial electricity demand ($E_{t,s}$) is a function of electricity price $P_{s,t}$, time-invariant state-specific factors (c_s), such as market regulations that often do not easily change, the other covariates ($X_{t,s}$) that affect electricity demand such as employment ($L_{t,s}^{emp}$), natural gas prices ($P_{t,s}^{NG}$), outside temperature ($W_{t,s}^{temp}$), and a random error term $\varepsilon_{t,s}$ that is assumed to be identically and independently distributed with zero mean and constant variance $\varepsilon_t \sim (0, \sigma^2)$:

$$E_{t,s} = c_s P_{t,s}^{\beta_1} X_{t,s}^{\beta_2} e^{\varepsilon_{t,s}} \tag{2.1}$$

where $X_{t,s} \in \{L_{t,s}^{emp}, P_{t,s}^{NG}, W_{t,s}^{temp}\}$.

Transforming the model by taking natural log, I get:

$$\ln E_{t,s} = \ln c_s + \beta_1 \ln P_{t,s} + \beta_2 \ln X_{t,s} + \varepsilon_{t,s} \tag{2.2}$$

Similar to the work of Houthakker (1974), Bohi and Zimmerman (1984), Gately and Huntington (2002), Bernstein and Griffin (2006), Erdogdu (2010), and Alberini and Flippini (2011), a dynamic transformation of the model can be made by assuming partial adjustment behavior (Liu, 2004). Suppose $E_{s,t}^{*}$ is the optimal demand for electricity which is unobservable to researchers:

$$\ln E_{s,t}^{*} = m_s + \beta_1 \ln P_{s,t} + \beta_2 \ln X_{s,t} + \varepsilon_{s,t} \tag{2.3}$$

Consumers may not be able to adjust instantly to the optimal amount of electricity consumed when the price fluctuates due to technological barriers (e.g., adjusting/adopting smart meters may take some time), production constraints (e.g., some industrial consumers cannot change their production schedule immediately in response to price changes), or tariffs and agreements (e.g., consumers may agree to purchase at a certain price during the year). Therefore, the dynamic relationship between the optimal electricity demand ($\mathrm{lnE}^*_{s,t}$) and the actual electricity demand ($\mathrm{lnE}_{s,t}$) is adjusted with δ as the coefficient. A larger δ implies faster adjustment to the optimal demand based on the actual demand (Liu, 2004):

$$\mathrm{lnE}_{s,t} - \mathrm{lnE}_{s,t-1} = \delta\left(\mathrm{lnE}^*_{s,t} - \mathrm{lnE}_{s,t-1}\right). \tag{2.4}$$

Substituting $\mathrm{lnE}^*_{s,t}$ into the equilibrium equation yields:

$$\mathrm{lnE}_{s,t} - \mathrm{lnE}_{s,t-1} = \delta\left(m_s + \beta_1 \mathrm{lnP}_{s,t} + \beta_2 \mathrm{lnX}_{s,t} + \varepsilon_{s,t} - \mathrm{lnE}_{s,t-1}\right). \tag{2.5}$$

The estimated equation becomes:

$$\mathrm{lnE}_{s,t} = \delta m_s + (1-\delta)\mathrm{lnE}_{s,t-1} + \delta\beta_1 \mathrm{lnP}_{s,t} + \delta\beta_2 \mathrm{lnX}_{s,t} + \delta\varepsilon_{s,t}\,. \tag{2.6}$$

Electricity price ($\mathrm{lnP}_{s,t}$) is endogenous because it is determined, in part, by the demand for electricity. It is thus correlated with the error term. Thus, I employ instrumental variables ($\mathrm{lnZ}_{s,t} = \mathrm{GSP}_{s,t}, \mathrm{P}_{s,t-1}$) that are correlated with the endogenous variable (i.e. electricity price) and uncorrelated with the error term in the first equation to estimate price of electricity. For instrument, I include annual Gross State Product (GSP) for all industries in each state, excluding the value added by utilities to address this issue. GSP measures the annual total value added by the industry at the state level. Change in industry value added increases electricity generation in a state, which affects the price of electricity. Change in electricity price affects electricity demanded but only through change in state industry value added. However, state GSP is a weak instrument. Thus, I add the lagged electricity price ($\mathrm{lnP}_{s,t-1}$) as an instrument, which affects the current price of electricity and ultimately electricity demanded[6]. The expected direction of impact is positive, an increase in the previous year's electricity price also increases the electricity price in the current year. Therefore, the estimated demand equation becomes:

$$\ln E_{s,t} = \delta c_s + \delta\beta_1 \ln P_{s,t} + \delta\beta_2 \ln X_{s,t} + \delta\beta_3 \ln E_{s,t-1} + \delta\beta_4 INTER_s + \delta\beta_5 YEAR_s + \delta\beta_6 DR_{s,t} + v_{s,t}, \quad (2.7)$$

where $Z_{i,s,t} = (GSP_{s,t}, P_{s,t-1})$, s = states, t = time, and i = index for instruments

The assumption that the error term is not correlated with the electricity prices or with other covariates in the model is tested: $Cov(\varepsilon_{s,t,}|P_{s,t}, X_{s,t}, c_s) = 0$. The instrumental variables $Z_{s,t}$ are also highly correlated with the endogenous variable, industrial electricity price ($P_{s,t}$), and uncorrelated with the error term $\varepsilon_{t,s}$ (Cov ($P_{s,t}, z_{s,t}) \neq 0$ and Cov ($\varepsilon_{s,t}, z_{s,t}) = 0$). I tested whether the identification restrictions are satisfied and whether the equations are weakly identified, using the Hansen-Sargan (1982) test statistics for validity of the identification restrictions (H_0: identification restrictions are satisfied). I use partial F-statistics (H_0: Equation is weakly identified) and Cragg-Donald Wald for identification (H_0: Endogenous regressors are unidentified) test. I present the test statistics in Appendix Table 2.2. The Hansen-Sargan statistic shows that identification restrictions are satisfied, the partial F-statistic shows that the instruments are not weak, and the Cragg- Donald Wald statistic is higher than the 10% tolerable bias level, which indicates that the endogenous regressors are identified.

The expected coefficient of the industrial price ($\ln P_{s,t}$) is negative. As price of electricity goes up, electricity demanded by the industrial customers should decrease. Further, I expect to find a positive relationship between one-year lagged electricity demand ($\ln E_{s,t-1}$) and the electricity

[6] One can be concerned about the correlation between the industrial sales per customer and the lagged industrial price. I test whether significant correlation between these two variables and there is not statistically significant correlation (Pairwise correlation is -0.0249). I present the first-stage regression results in Appendix Table 2.6.

demand in the current year ($\ln E_{s,t}$) because I expect industrial customers to, at minimum, maintain their industrial production. Therefore, I would observe strong persistence in the electricity demand from year to year. If the current electricity demand is high, it would increase expected future electricity demand. The natural gas price ($\ln P_{s,t}^{NG}$) delivered to the industrial customers is included as an alternative fuel to electricity. However, the expected impact of the natural gas prices in industrial electricity demand is ambiguous. In the majority of the residential electricity demand studies, natural gas prices are usually found to be a substitute for electricity because there are significant numbers of customers using gas for heating their homes. However, industrial processes may also use natural gas along with electricity. Therefore, the net effect can only be determined empirically. I also include the total number of employees in the manufacturing sector ($L_{t,s}^{emp}$) as a socioeconomic variable to control for the size of the industry in each state. Similar to the natural gas prices, the net effect of the number of employees in manufacturing on industrial electricity demand is ambiguous. Electricity demand may be lower in in the states with labor-intensive manufacturing industries. For example, cement manufacturing industry is one of the largest energy intensive manufacturing industries while the amount of labor used during the production process is quite small (KEMA 2005). A study by Cox et al. (2013) also found that labor intensity and electricity consumption are substitutable inputs in manufacturing sector. On the other hand, a large number of employees may signify a big manufacturing sector in a state and hence, electricity demand may be higher. Finally, I include temperature ($\ln W_{t,s}^{temp}$) to control for the effect of the outdoor temperature on industrial electricity demand. I expect to find a small positive effect on industrial electricity demand because industrial customers do not change the bulk of their electricity consumption with respect to changes in weather conditions.

As an indicator for the effect of industrial demand response ($DR_{s,t}$) on electricity demand in the retail market, I estimate the impact of potential peak demand reduction and actual peak demand reduction on industrial electricity demand. I expect lower electricity demand with higher amount of industrial potential peak demand reduction. Similarly, with higher compliance in peak demand reduction, industrial demand is expected to decrease.

I control for all the years ($\mathrm{YEAR_S}$) between 2000 and 2013, where 2013 is the omitted category. I expect to find lower electricity demand in all of the years relative to 2013 assuming that industrial electricity demand increases over time. Finally, I include an interaction term of the state dummy variables with price ($\mathrm{INTER_s} = \mathrm{state} * \ln \mathrm{P_{s,t}}$) in order to capture the state-elasticity estimated per state and we expect to find negative price elasticity of demand in each state as well. I summarize these hypotheses on the variable coefficients in Table 2.1.

Table 2. 1: Expected Coefficients of the Regression Variables

Variable	**Hypotheses**	**Expected Sign**
Electricity Price	Increase in industrial electricity price decreases electricity demanded by the industrial customers	-
Industry GSP	Increase in industrial value-added increases demand for electricity, which increases electricity price that industrial customers face	+
Lagged Electricity Load	Higher industrial electricity demand during the previous year increases the industrial electricity demand in the current year	+
Number of Employees	Electricity demand is lower in labor-intensive manufacturing processes	+/-
Natural Gas Price	Increase in industrial natural gas prices increases/decreases electricity demand	+/-
Temperature	Electricity demand is higher in higher outdoor temperature	+
Potential Peak DR	Increase in industrial potential peak demand reduction capacity decreases industrial electricity demand	-
Actual Peak DR	Increase in industrial actual peak demand reduction capacity decreases industrial electricity demand	-

2.3.2 Real-Time Wholesale Market Model

In the wholesale market, power generating and distributing electric utilities and load serving aggregators buy and sell electricity in an hourly market. I assume a Cobb-Douglas functional form for the real-time wholesale demand, where $E_{h,d}$the real-time electricity is demand and $P_{h,d}$ is the real-time price for electricity in the wholesale market:

$$E_{h,d} = \beta_0 P_{h,d}^{\beta_1} e^{\omega_{h,d}}. \tag{2.8}$$

Transforming the model by taking the natural log, I get:

$$\ln E_{h,d} = \beta_0 + \beta_1 \ln P_{h,d} + \omega_{h,d}. \tag{2.9}$$

Real time market dispatches every five minutes during all hours of a day. Power plants that are committed to serve electricity in the real-time market are determined in every five minutes. These dispatches and responses are monitored by the MISO market. The committed power plants will decide the amount of electricity they are going to supply at a certain price in the next five minutes in the real-time market. Electricity buyers in the real-time market may not instantaneously respond to real-time price changes because electricity supply is updated every five minutes. Expected demand is subject to available power plant capacity at that hour as well as the system conditions (e.g. congestion) in current hour. Therefore, the anticipated electricity demand in the following hour is informed by the current demand. Following the similar steps for the equations 2.3 through 2.7, the real-time electricity demand becomes:

$$\ln E_{h,d} = \beta_0 c_d + (1-\delta)\ln E_{h,d-1} + \delta\beta_1 \ln P_{h,d} + \delta\omega_{h,d}. \tag{2.10}$$

Considering the endogeneity due to the relationship between real-time price and real-time electricity demand, I use instruments for real-time price. I use hourly temperature for all MISO states ($\ln TEMP_{h,d}$) as instrument for the price of electricity ($\ln P_{h,d}$), where $h =$hours of a day and $d =$days. I include hourly lagged real-time electricity price ($\ln P_{h-1,d}$) into the first-stage of the estimation. Consequently, the estimated equation with instrumental variables is:

$$
\begin{aligned}
\ln E_{h,d} = \beta_0 + \text{trend} + \beta_1 \ln P^{*}_{h,d} + +\beta_2 \ln P^{2}_{h,d} \\
&+ \beta_3 \ln E_{h-1,d} + \beta_4 PEAK_{h,d} + \beta_{5g} HOURS_g + \beta_{6i} DAY_i + \beta_{7m} MONTH_m + \beta_{8j} YEAR_j + \beta_9 LWY_y \\
&+ \beta_{10} TG_y + \beta_{11} \text{intermintemp} + \beta_{12} \text{intermaxtemp} + \gamma_{13} DR_{h,d} \\
&+ \theta_{h,d}. \qquad (2.11)
\end{aligned}
$$

In the second stage, I include a squared term of the real-time prices ($\ln P^2_{h,d}$), expecting to find a positive coefficient because the responsiveness to real-time price changes is expected to be increasing at decreasing rate (e.g., the responsiveness to large spikes in market prices should be lower than price responsiveness to small increase in the real-time price). Additionally, I include an interaction term with real-time prices and dummy variables for the peak hours ($PEAK_{h,d}$) of each day between 8am and 10pm; dummy variables for the last week of December (LWY_y) and for Thanksgiving day (TG_y) for each year y, which are two of the highest electricity consumption times of the year; and dummy variables for hours ($HOURS_g$) where g=1,2...,24, days (DAY_i) where i=1,2…,31, months ($MONTH_m$), where m=1,2…,12 and years ($YEAR_j$), where j=2008, 2013. Finally, I include an interaction term of real-time price elasticity with the dummy variables, which takes the value “1” during maximum and minimum temperature during peak hours (intermintemp, intermaxtemp), a monthly trend. $\theta_{h,d}$ is the random error term that is assumed to be identically and independently distributed with zero mean and constant variance $\theta_{h,d} \sim (0, \sigma^2)$. I expect to find very small price responsiveness during extreme temperatures because there is high demand for electricity during very cold and hot times. However, during extremely cold winter or extremely hot summer days, electricity intensive manufacturing processes may demand more electricity in order to avoid any interruption in the machinery or inventory. Large manufacturing plants may have a smaller responses to real-time price changes (e.g., food manufacturing plants may be sensitive to extremely hot temperatures or machinery can be broken as a result of freezing temperatures). Similarly, residential customers consume higher amount of electricity during especially extremely hot temperatures during summer due to air conditioning needs.

Further, I obtain information on the timing of the system peak demand events in MISO between 2008 and 2013. I include these dates and hours interacting with the real-time prices ($DR_{h,d}$) and estimate the price elasticity at those specific DR event hours. These DR events include extreme weather events and emergency system reliability reductions. For example, I control for the extreme cold weather event that occurred on January 22, 2013. I present the DR events dates in Appendix Table 2.5.

The estimation procedure includes different times of day. First, I estimate the price elasticity of demand for a day, controlling for all hours of the day by including dummy variables for each hour. I then estimate price elasticity of demand for on-peak hours. I define two different on-peak hours: between 8am and 10pm, and between 3pm and 8pm. Daily peak in MISO is usually assumed to be between 8am and 10pm. However, the majority of the system congestion has historically occurred between 3pm and 8pm. I also estimate the price elasticity of demand for DR event days only. Finally, I estimate price elasticity of demand for off-peak hours (i.e., hours outside of 8am to 10pm). I estimate the price elasticity of the wholesale market for the years between 2008 and 2013. I also estimate the two-stage model for the Illinois hub, the Minnesota hub, and the Michigan hub separately.

In the first stage, I expect that the real-time price will increase with higher temperatures in MISO states. In other words, the relationship between the hourly temperature variables and the real-time price is expected to be positive. I expect to find a negative real-time price elasticity of demand in the second-stage for all of the estimations. Further, I expect to find higher price-responsiveness from the estimations of different on-peak hours and DR events, which is consistent with the hypothesis that demand response serves as a resource to reduce peak demand during on-peak hours. Assuming that utility-based programs are targeting retail customer during high load hours, wholesale market participants are expected to be more responsive during on-peak hours. . I also expect to find a positive relationship between the hourly electricity demand and peak hour dummies as well as last week of the year and Thanksgiving days. I summarize my hypotheses on the variable coefficients in real-time market model in Table 2.2.

Table 2. 2: Expected Coefficients of the Regression Variables

Variable	**Hypotheses**	**Expected Sign**
Real-Time Price	Increase in real-time electricity price decreases electricity demanded	-
Hourly Temperature	Real-time price of electricity is higher at higher prices	+
Peak Hours*Price	Increase in real-time price during peak hours decreases electricity demanded	-
DRevent*Price	Increase in real-time price during DR events decreases electricity demanded	-
MinTempDum*Price	Increase in real-time price during extremely cold temperatures decreases electricity demanded	+/-
MaxTempDum*Price	Increase in real-time price during extremely hot temperatures decreases electricity demanded	+/-
Holiday Dummies	Real-time electricity demand is higher during holiday (e.g., last week of December and Thanksgiving days)	+

2.4.Data

2.4.1 Retail Market Data

The primary data source for the annual industrial demand analysis was the Energy Information Administration (EIA) 861 Electric Power Annual Reports, which includes utility-level electricity distribution data to the residential, commercial, industrial, and total electricity consumers. Data includes state electricity sales to the industrial sector. I also retrieve industrial retail electricity prices from the same dataset. I aggregate the utility level sales data at the state level and obtain total industrial sales, revenues, and the number of industrial electricity customers for 13 states across the MISO footprint between 2000 and 2013. Industrial and total electricity prices vary across states and over time. I adjust these prices to real industrial and real total electricity prices using an annual GDP deflator (The World Bank 2013). Between the years 2000 and 2013, the average annual electricity sold to industrial consumers was 2,984MWh per customer[7], including the highest electricity sales to Illinois (7,493MWh/customer) and the lowest electricity sales to Nebraska (343MWh/customer). Between 2000 and 2013 the annual average electricity price was 52 dollars/MWh, the highest average electricity price was 62 dollars/MWh in Michigan, and the lowest average electricity price was 42 dollars/MWh in Kentucky.

I obtain peak demand reduction data also from EIA Reports. The maximum peak demand reduction capacity and the actual peak demand reduced vary across the states. States typically did not fully use their potential peak demand reduction capacity. Figure 2.3 shows the actual peak demand reduction in 2013[8]. Actual peak demand reduction was significantly lower in some states (e.g., North Dakota). Some states with lower actual peak demand reduction have almost reached the potential maximum capacity (e.g. Ohio).

[7] In order to capture the state size effect, I scale the industrial sales with the total number of industrial customers for each state. Therefore, the estimation includes industrial demand per average customer.
[8] Here I only report DR figures for 2013 but aggregate DR potential peak and actual demand reduction comparison is provided in the Discussion Section.

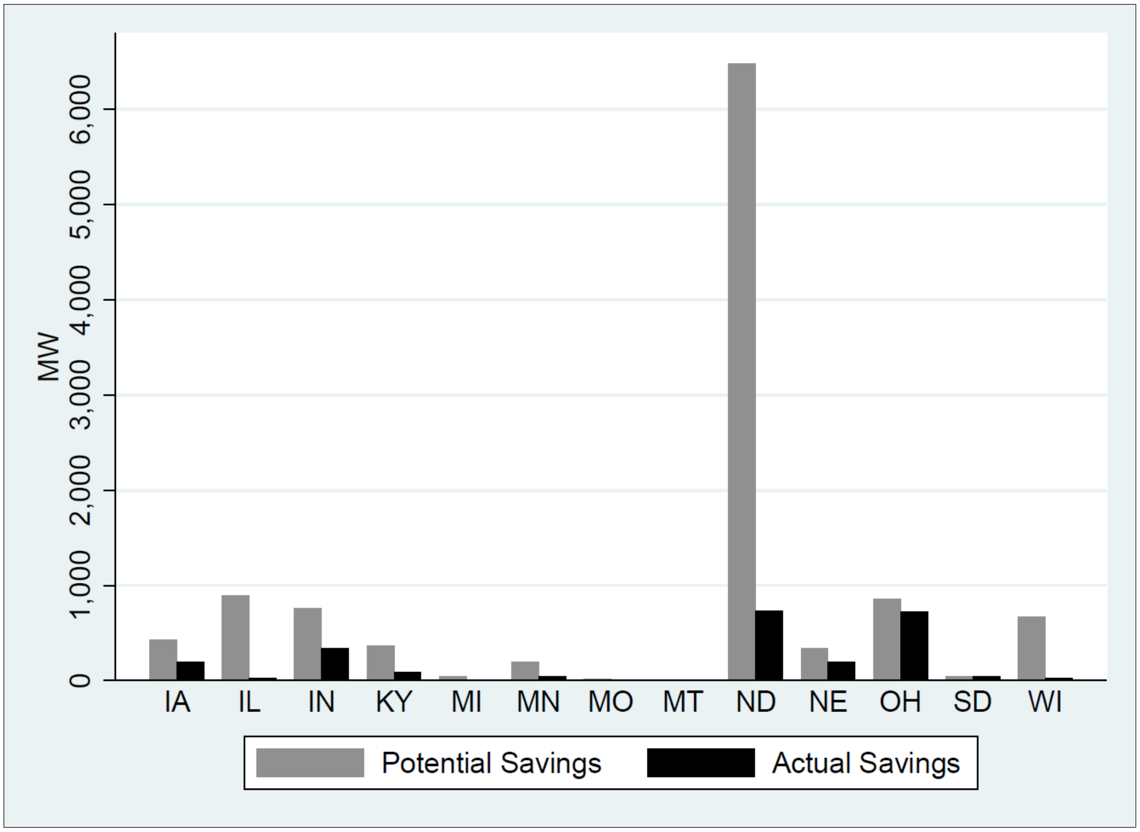

Figure 2. 3: Compare Peak and Actual Industrial Demand Savings (MW) in 2013

In 2013, the average number of industrial customers enrolled in demand response programs was 837 and there were 776 industrial customers with dynamic pricing programs in the MISO footprint. The average industrial potential peak demand reduction is 854MW and the average actual peak demand reduction was 186MW in 2013. I summarize the descriptive statistics of the retail market variables in Table 2.3.

Table 2. 3: Summary Statistics for Annual Industrial Data 2000-2013

Variable	Description	Notation	Mean	Range
Price (dollars/MWh)	Average* Electricity Prices	$P_{t,s}$	50.4	[30.01-70.7]
Ind. Electricity Sales Per Customer (MWh)	Amount of Electricity Sold per Industrial Customer	$E_{t,s}$	2,984	[200-9,781]
Temperature (°F)	Annual Temperature	$W_{t,s}^{temp}$	48.4	[38.3 - 58.5]
Industry GSP ($ million)	Gross State Product All Industries without Utility	$GSP_{t,s}$	218,7 95	[17,702 - 710,409]
Industry size (thousand)	Number of Employees in Manufacturing Sector	$L_{t,s}^{emp}$	339	[17- 1,021]
Natural Gas Price ($/thousand cubic feet)	Industrial natural gas prices	$P_{t,s}^{NG}$	7.14	[2.75-12.71]
Potential Peak DR (MW)	Potential Peak Demand with DR	DRPotentialCap	854	[0-6,482]
Actual Peak DR (MW)	Actual Peak Demand Reduced with DR	DRActualCap	186	[0-728]

Number of Observations=182
*****Average over all utilities in each state

2.4.2 Wholesale Market Data

The MISO wholesale market data includes real-time locational marginal prices (LMPs) and hourly load generation for the years 2008 and 2013.[9] Real-time LMPs represent the additional value of an electricity load delivered to a specific LMP node, which is called the Critical Pricing

[9] For the hourly data after December 13, 2013, the MISO changed their reporting regions; therefore, to maintain consistency, I did not include data after this date.

Node (CPN) in the MISO. The temperature data includes the hourly average of all climate stations at the states across the MISO footprint. Table 2.4 summarizes the wholesale market data for 2008 and 2013.

Table 2. 4: Summary Statistics for Wholesale Market Data 2008 and 2013

Variable	Description	Mean 2008	Range 2008	Mean 2013	Range 2013
Electricity load (MWh)	Amount of electricity	63,881	[43,294 - 97,060]	58,197	[38,181-95,400]
Real-time electricity price ($/MW)	Hourly real-time price of electricity	48	[-240 - 451]	30	[-29 - 929]
Temperature (°F)	Hourly temperature	45.8	[-3.9 - 84.5]	46.2	[-3.3 - 88.3]
Min Temperature (°F)	Hourly minimum temperature	45	[-5 - 84]	45.1	[-3.9 - 87.2]
Max Temperature (°F)	Hourly maximum temperature	47	[-3.2 - 84]	47.3	[-2.5 - 89.2]
Number of observation: 8764 for each year					

2.5 Results

2.5.1 Annual Retail Market Estimation Results

I capture the state fixed-effects with the dummy variables generated for each state and calculate elasticity values by summing parameter coefficients on industrial price ($\ln P_{s,t}$) and state interaction dummies ($INTER_S$): $\delta\beta_1 + \delta\beta_4$ (Equation 2.7) for the retail market. Elasticity estimates for the retail industrial customers vary across the states and state elasticity estimates ($\beta_1 + \beta_4$) for the industrial consumers range between (0.08-0.42), which is within the range estimated by previous studies. Industrial price elasticity estimates in the states show that a 10% increase electricity prices in a state is associated with a decrease in industrial electricity demand per average customer by about 2.7% in Iowa, 2.3% in Illinois, 2.4% in Indiana, 2.7% in

Kentucky, 4.2% in Michigan, 3.6% in Minnesota, 3.0% in Missouri, 0.8% in Montana, 2.1% in Nebraska, 2.2% in North Dakota, 2.9% in Ohio, 1.6% in South Dakota and 1.1% in Wisconsin. Table 2.5 summarizes annual industrial retail market estimation results including two-stage estimation[10] with the potential peak demand reduction and actual peak demand reduction with demand response programs offered to the industrial customers in the MISO footprint. I also include the estimated state-specific elasticity estimates in Table 2.6. I jointly test the null hypothesis that state-elasticity estimates are not statistically different across the states using F-test. I reject the null hypothesis (H_0: $\delta\beta_{4,IA}\mathrm{INTER}_{IA} = \delta\beta_{4,IL}\mathrm{INTER}_{IL} = \cdots = 0$) that state elasticity estimates are not different with 15% significance level (F-stat: 2.51; Prob > chi2: 0.1158). Individual state price elasticity estimates are significant at least at the 10% level except for Illinois, Montana and Wisconsin. Figure 2.4 shows the price elasticity estimates for industrial customers in the states of the MISO footprint.

[10] Comparison of the OLS and instrumental variable estimation results are presented in Appendix Table 2.4.

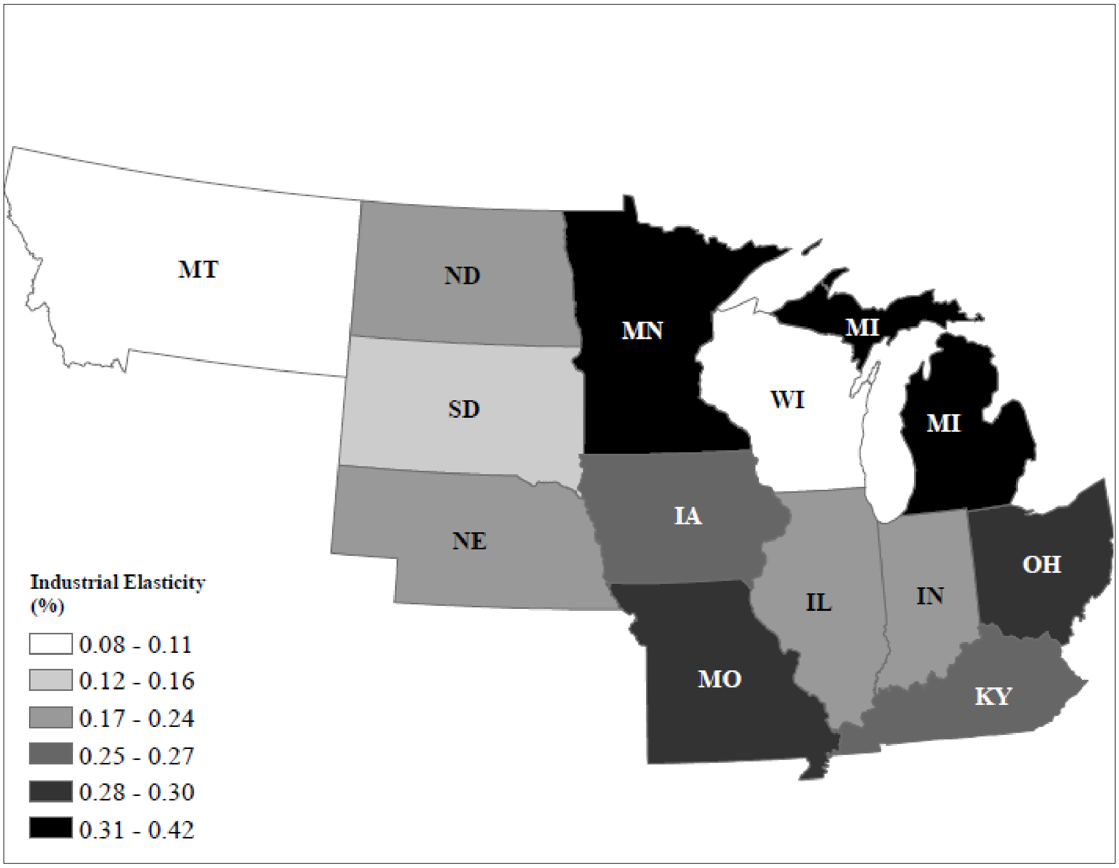

Figure 2. 4: Industrial Price Elasticity Estimates in Retail Market

The effect of the potential peak demand reduction is significant at the 15% significance level while actual peak demand reduction is significant at 10% significance level with respect to annual retail market electricity demand per customer (See Table 2.5). The effects of potential peak demand reduction capacity and actual peak demand reduction on electricity demand by industrial customers are quite small and similar in magnitude. A 10% increase in the industrial actual peak demand reduction capacity is associated with about 0.19% lower industrial electricity demand. This suggests that the industrial customers in the retail market might become more capable of managing electricity consumption with regard to price changes, likely through their increased understanding of their energy requirements as part of planning and assessment necessary to determine the value of demand response program participation.

If there is a 10% increase in the number of employees in the manufacturing sector, industrial electricity demand decreases by 5.9%. Based on the regression results, natural gas is a substitute for electricity (i.e., estimated coefficient is positive). If there is 10% increase in natural gas prices, electricity demand increases by 1.4%. However, the coefficient estimate is not significantly different from zero. A 10% increase in industrial electricity demand in the previous year significantly increases industrial electricity demand by about 5.4%. Finally, industrial electricity demand is about 1.9% higher with a 10% increase in outdoor temperature but the effect of outdoor temperature on electricity demand is insignificant. The signs of the explanatory variables are consistent with our initial hypotheses including the coefficients on the year and state interaction dummy variables.

Table 2. 5: Results from Annual Industrial Retail Models

	Potential Peak DR Capacity	Actual Peak DR Capacity
Real Industrial Price	-0.109	-0.169*
	(-1.05)	(-1.52)
Lagged Industrial Sales	0.548***	0.574***
	(3.56)	(3.81)
Manufacturing Employment	-0.592*	-0.656**
	(-1.87)	(-2.05)
Real NG Price	0.140	0.156
	(1.07)	(1.14)
Temperature	0.190	0.208
	(0.24)	(0.25)
Potential Peak Reduction	-0.019**	
	(-2.33)	
Actual Peak Reduction		-0.019*
		(-1.67)
R-square	0.638	0.637

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Table 2. 6: Regional Elasticity Estimates Retail Market

State	Coefficient	Std. Error	T	P>|t|	[95% Conf. Interval]	
Iowa	-0.27**	0.09	-2.89	0.05	-0.46	-0.09
Illinois	-0.23	0.17	-1.41	0.16	-0.57	0.09
Indiana	-0.24*	0.10	-2.42	0.02	-0.44	-0.04
Kentucky	-0.27***	0.07	-3.92	0.00	-0.41	-0.14
Michigan	-0.42***	0.13	-3.26	0.00	-0.68	-0.17
Minnesota	-0.36***	0.12	-3.04	0.00	-0.59	-0.12
Missouri	-0.30***	0.09	-3.30	0.00	-0.48	-0.12
Montana	-0.08	0.08	-0.93	0.35	-0.24	0.09
Nebraska	-0.21*	0.09	-2.45	0.02	-0.38	-0.04
North Dakota	-0.22*	0.09	-2.32	0.02	-0.40	-0.03
Ohio	-0.29***	0.10	-2.95	0.00	-0.49	-0.10
South Dakota	-0.16**	0.09	-1.70	0.09	-0.35	0.03
Wisconsin	-0.11	0.10	-1.05	0.30	-0.32	0.10

*WI is the reference category

I also test for whether the elasticity estimates at different hubs are different and I check for the validity of the instruments for the wholesale market model. Appendix Table 2.3 presents the test results for the instrumental variables. The Hansen-Sargan statistic shows that identification restrictions are satisfied, partial F-statistic shows that the instruments are not weak and Cragg- Donald Wald that endogenous regressors are identified based on the 10% tolerable bias level.

2.5.2 Real-time Wholesale Market Estimation Results

I calculate price elasticity in the real-time wholesale market by summing the coefficient estimates of hourly real-time price ($\ln P_{h,d}$), squared price ($\ln P_{h,d}^2$) and the interaction term of peak hours and real-time price ($\beta_1 + 2 \cdot \beta_2 + \beta_4 \cdot PEAK$)[11] (Equation 2.12). I present estimation results of price elasticity estimates for the entire MISO market, as well as Minnesota, Illinois and Michigan

[11] This is derived from the first order conditions of Equation 2.10. For different estimations provided in Table 8, I follow the similar approach if there is additional interaction terms included into the regression.

hubs at different times-of-day between 2008 and 2013 in Table 2.7 in Results section below. I present the bootstrapped standard errors (StataCorp, 2013).

Table 2. 7: Regional Elasticity Estimates Wholesale Market 2008 and 2013

Time-of-Day/ Location	**All Day**	**On Peak Hours 8am – 10pm**	**On Peak Hours 3pm-8pm**	**DR Event**	**Off-Peak**
MISO	-0.09***	-0.214***	-0.147**	-0.06*	-0.06***
	(8.66)	(10.42)	(6.18)	(1.85)	(4.82)
Minnesota Hub	-0.107*	-0.209***	-0.167***	-0.086	-0.064**
	(1.95)	(8.32)	(5.94)	(1.61)	(3.36)
Illinois Hub	-0.12***	-0.144***	-0.098**	-0.063	-0.14***
	(5.31)	(3.92)	(2.68)	(1.27)	(3.29)
Michigan Hub	-0.103***	-0.120***	-0.160***	-0.135*	-0.008
	(5.95)	(2.81)	(3.58)	(1.72)	(0.56)

t-statistics in parenthesis * p<0.1 ** p<0.05 *** p<0.01

The price elasticity of hourly electricity demand is relatively small in the wholesale market as compared to the retail market. In the MISO electricity market between 2008 and 2013, a one percent increase in real-time price was associated with 0.09% decrease in hourly electricity demanded. Real-time price responsiveness is significant for all hours at 1% significance level. During on-peak hours and DR events, there is also significant response to real-time price changes. Electricity demanded is reduced by about 0.15% between 3pm and 8pm and by 0.06% during a DR event with a one percent increase in the real-time price in the MISO market. During off-peak hours, a one percent increase in the real-time price leads to a 0.06% reduction in electricity demanded.

At specific pricing hubs, Minnesota, Michigan and Illinois, I find higher daily price responsiveness compared to the overall MISO estimates. One percent increase real-time price decreases electricity demanded by 0.11% in Minnesota hub, 0.12% in Illinois and 0.10% in Michigan. I also find significant response during on-peak hours at these hubs as well, where

Minnesota has the highest real-time price responsiveness and Michigan has the lowest price responsiveness between 8am and 10pm. However, during a DR event, I only find weak price responsiveness at Michigan hub while Minnesota and Illinois hubs does not show any evidence of price responsiveness. A one percent increase in real-time price during off-peak hours is associated with a significant reduction in electricity demanded by 0.064% in Minnesota and 0.144% in Illinois hub.

The interaction terms on maximum ($\mathrm{intermaxtemp}$) and minimum ($\mathrm{intermintemp}$) temperature during peak hours are statistically significant for the MISO market and all pricing hubs. The sign of the coefficient is statistically significant and negative for both of the variables $\mathrm{intermintemp}$ and $\mathrm{intermaxtemp}$. The magnitude of the impact on the electricity demanded is negligible however. This result suggests that there is responsiveness to price changes during extreme temperatures but not as much as during average temperatures. This finding is consistent with the initial hypothesis is that it is hard to give up on the electricity consumption during extremely cold or hot days for the real-time market participants. Electricity demand is also significantly influenced by the short run electricity demand. A 10% increase in the previous hour's electricity consumption increases electricity demand by 9.7% for the MISO electricity market. Finally, hour time dummies are statistically significant for almost each hour between 8am and 10pm, and time dummies for Thanksgiving and the last week of the year are significant for the whole MISO market and other pricing hubs. The direction of the impacts of the interaction terms, time dummies, and short run electricity demand was the same for both 2008 and 2013.Complete real-time market results for MISO are presented in Appendix Table 2.7.

2.6 Discussion

Utility electricity rates are determined based on generation, transmission and distribution costs in a highly regulated environment. State policies toward the integration of demand response resources at the retail level across the U.S. have grown rapidly in the last decade, responding to and influencing increasingly competitive retail market environments- especially in electricity markets like PJM and NYISO (Walawalkar et al., 2010). However, particularly in the heavily regulated MISO states, retail demand response program adoption and implementation – specifically among the industrial sector – has been relatively slow. While operating at different temporal and spatial scales, MISO has advanced innovative wholesale market rules addressing geographic variation across generation, transmission, and distribution resources operating in day-ahead, minute and sub-minute markets. The empirical analysis employed in this essay aims to explore the connection between the retail electricity market, in which industrial consumers often purchase electricity through relatively flat retail rates, and the wholesale electricity market, where market participants are able to change their electricity transactions based on real-time price changes. Although I was not able to directly estimate the causal relationship between the retail and wholesale price responsiveness with the existing data, my empirical analysis found evidence that industrial retail customers respond to price changes across MISO states and that the magnitude of price-responsiveness varies by state. Further, there is evidence of significant real-time price responsiveness in the wholesale market during on-peak hours, when the utility based dynamic pricing programs are often implemented. In addition, this price responsiveness is strongest in sub-regions where long-term industrial retail price-responsiveness is highest (i.e. Michigan and, to a lesser extent Minnesota). Customer exposure to real-time price signals at the retail level is limited and, consequently, affects demand serviced through wholesale transactions. Moreover, the level of regulation and demand response adoption varies by state – hence, the implications for industrial demand response programs will likely be different in each state. For example, Minnesota has a strongly regulated electricity market, creating barriers to transacting bundled demand response resources. But, it also has the largest number of customers agreeing to provide demand response capacity in large part due to relatively high incentives for industrial customer participation. Minnesota's estimated retail industrial price elasticity of electricity demand as well as on-peak price-responsiveness in the wholesale market is higher compared to relatively deregulated states such as Illinois and Ohio. Also, Minnesota has the highest total peak demand reduction capacity compared to Illinois and Michigan. Illinois, which is one of the deregulated states in MISO footprint, has relatively inelastic industrial demand in the MISO footprint. The capacity for dynamic pricing for Illinois industrial customers is also the smallest among the three pricing hubs, the number of customers that is enrolled in dynamic pricing programs are not as high as Minnesota, and real-time price responsiveness is lower at the Illinois hub compared to the Minnesota hub. In Michigan, I observe a significantly higher price-responsiveness during on-peak hours and insignificant response during off-peak hours, while retail industrial price-responsiveness in Michigan is estimated to be the highest in the MISO footprint. Also, the aggregated DR capacity in Michigan is the highest after Minnesota. Table 2.8 provides a comparison of the industrial retail and real-time elasticity estimates as well as the total peak demand reduction capacity between 2000 and 2013 across Minnesota, Illinois and Michigan.

Table 2. 8: Comparison of Regional Elasticity (absolute values) and Total DR Capacity

Elasticity/ Location	Industrial Retail Elasticity	Wholesale Elasticity Peak Hours 3pm-10pm	Wholesale Elasticity DR Event	Aggregated DR Capacity(GW) 2000-2013
Minnesota	0.36***	0.167***	0.086	13,341
Illinois	0.23	0.098**	0.063	4,456
Michigan	0.42***	0.120***	0.135*	6,059

Note: Elasticity values are in absolute terms and * $p<0.1$ ** $p<0.05$ *** $p<0.01$

Many states already have established price and incentive based demand response programs to some extent, but the contribution of peak demand reduction by the industrial customers is so small that the system wide industrial demand response implications are negligible. Although the analysis demonstrates that industrial customers respond to price changes, more industrial peak demand reduction may contribute to larger reductions in industrial electricity consumption. This could be motivated by looking closely into the differences in types of industries and differences in electricity demand profiles in a particular state. Therefore, demand response program design should consider the spatial and sectorial differences to involve more industrial customers in demand response programs.

Finally, in order to make demand response more efficient in the retail electricity market, consumers will likely need to be more fully exposed to price signals from the wholesale market. This requires additional transparency of information between the wholesale and retail markets. The analysis looks at electricity demand at the retail and wholesale markets, and I find differences in the magnitude of the price responsiveness between the two markets. However, in both markets, I find significant price responsiveness. Results suggest that retail industrial customers respond significantly to price changes at a time scales commensurate with current longer-term pricing contracts. Results also suggest that generation and distribution utilities transacting at the wholesale level are able to respond in modest ways to real-time price changes, even without the demand-pull of a price-informed retail market. While it is not realistic to expect all retail customers to engage as wholesale market participants (Sioshansi and Vojdani 2001), industrial consumers with elastic demand may benefit significantly by participating dynamic pricing programs and the system will also likely benefit. In fact, previous studies have pointed out that the electricity system benefits more from lower average electricity prices when only a small number of customers with flexible electricity demand respond to price changes (Kirschen 2003, Caves et al. 2000).

Current dynamic pricing programs, particularly in the MISO region, have not attempted to target industrial demand based on price responsiveness. This essay suggests that industrial customers respond to price changes differently across state regulatory environments and that wholesale price elasticities are highest in areas where industrial price responsiveness at the retail level is highest. Future research is needed to better understand industrial load across states to determine whether regional peak demand reduction by a targeted cluster of large energy users in certain parts of the footprint may contribute market-level efficiencies. Industrial adoption and efficiency of demand response policies could be improved by understanding the implications of these results. Policy designers could identify those actors most able to respond to price signals and target fewer but more responsive, participants.

2.7 Conclusions

This essay estimates electricity demand in the retail and wholesale electricity market by employing a two-stage least squares estimation approach. I first analyze the industrial customers in the retail market at the state level, considering the state demand response programs offered by the utilities. I find that there is variation in retail industrial electricity demand across the states. At the wholesale level, I estimate the market demand at different pricing hubs in the MISO region, and I find lower price elasticity in the wholesale market than in the retail market. Although price responsiveness varies across these two markets, I find a similar pattern in the demand response implementation in Minnesota, Illinois and Michigan. Regions that are price-elastic tend to have more demand response adoption, particularly more dynamic types of demand response adoption (e.g., real-time pricing). This essay also points out that regional differences and customer diversity should be taken seriously before designing uniform demand response programs for the whole system. Future research is needed to build improved understanding of industrial customers in different sectors and explore industrial price responsiveness and adoption of demand response across state regulatory and regional market governance environments. The empirical approach in this essay could be considerably improved with more granular consumer-level data.

Chapter 3

Integration of Residential PV and Its Implications for Current and Future Residential Electricity Demand in the United States

3.1 Introduction

After the federal government passed the Energy Policy Act in 2005, U.S. energy policy shifted towards fostering renewable energy investments. State level policies followed, incentivizing the renewable energy technologies and electricity generation from renewable resources. For example, state Renewable Portfolio Standards (RPS), one of the most successful state level policies for renewable energy developments, have promoted renewable energy generation since late 1990s by requiring states to generate a certain portion of their electricity from renewables (Wiser et al., 2007).

Wind has been one of the most widely adopted renewable resources and it currently has the highest share in the renewable energy portfolio. The wind sector is now considered to be a mature industry (Dismukes 2012). Solar energy, however, is still an emerging technology, and could potentially lead to a sustainable electricity generation across the country (Wiginton et al. 2010). Residential rooftop solar penetration in the U.S. has increased significantly over the past decade. In the last quarter of 2012, residential rooftop PV capacity installations have exceeded 1.5 GW in the U.S. The projected increase in distributed generation capacity by residential solar is 9 GW by 2016 and 20 GW by 2020 (APPA, 2013).

While state RPS policies incentivized utilities to generate renewable electricity, their impact has been limited in terms of customer-based distributed solar generation (Borchers et al., 2014). Federal investment tax credits (ITC) and state net energy metering (NEM) regulations have played a more important role in the development of distributed generation. Decreasing installation costs, technological advancements, alternative financing options and state and federal incentives have contributed to increasing trends for investments in residential solar in the U.S (ICF International, 2010). For instance, solar installation costs have decreased by roughly 70 percent since 2008, and federal tax credits have reduced initial installations costs for solar by about 30 percent[12] (APPA, 2013). Third party solar is also becoming a popular financing option; it stimulates development of residential solar by offering residential customers the opportunity to generate electricity from solar without purchasing the equipment. Third party solar has two financing models: (1) power purchase agreement (PPA) and (2) lease. Neither models requires an initial investment cost. The PPA model offers customers an offset in their electricity bill in return to the electricity generated by the solar system. Developers typically sell that electricity to the customers for a lower rate (SEIA 2014a). The leasing model is designed as a contract between the customer and the developer. The customer pays a fixed monthly fee for solar energy generated and does not for the solar energy portion of the electricity (SEIA 2014a). The third-party solar financing has been an important catalyst of the increasing residential solar penetration. For example, about 90% of the residential solar in New Jersey was through third-party solar agreements as of 2013 and in states like California, Arizona and Colorado, third-party distributed generation is more than 60 percent (SEIA, 2014a) of total solar energy consumption.

Distributed generation has a number of potential benefits including clean energy generation, avoided peak generation capacity, avoided or deferred transmission and distribution capacity investments reduced transmission line losses due to proximity to the generator source and lower customer bills due to generating electricity on-site (Chiradeja, 2004; Pepermans et al., 2005; Darghouth et al., 2012; APPA, 2013). On the other hand, increased penetration of distributed generation creates challenges for the electric utilities as their sales decline. Dubbed as

[12] Federal tax credit will step down to 10 percent from 30 percent in 2017.

a “death spiral” by some industry experts, as more customers adopt distributed generation, utilities’ costs to maintain and operate the grid must be spread across a smaller customer base, raising customer rates and increasing the economic incentive to opt for more distributed generation (Kind, 2013; Costello and Hemphill, 2014). Utilities also argue that distributed generation creates a fairness issue with transferring the transmission, distribution and reliability costs to the customers without distributed generation technologies (Raskin, 2014). More specifically, customers with distributed generation (i.e., rooftop solar) reduce the amount of electricity they purchase from the grid but they still rely on the grid due to the intermittency of rooftop solar. This implies that they pay less than their fair share for the system’s fixed costs while the utilities maintain their fixed costs for generation, transmission and distribution (Stanton, 2013).

Several studies have looked at the costs and benefits of distributed generation, and the role that state and federal incentives have played on accelerating renewable energy investments in the U.S. A study by Crago and Chernyakhovskiy (2014) studied the effectiveness of the state policies that incentivize solar PV adoption in the U.S. The results of their empirical analysis showed that policies (e.g., sales tax exemptions, income tax credits, loan financing programs and cash rebates) increase the capacity for solar PV, particularly the policies that are specifically targeting solar PV technology (Cai et al., 2013). Recent studies also showed that future residential load profiles are likely to decrease with the penetration of various technologies such as residential PV, combined heat and power, heat pump storage and electric vehicles (Veldman et al., 2013; Bediako et al., 2014). Their scenario analysis showed that residential PV penetration is projected to grow and that future residential load profiles, particularly summer load profiles, will be significantly affected by distributed generation. Most of simulations in these studies have shown that the residential electricity demand is reduced with the adoption of various combinations of residential PV, combined heat and power, heat pump storage and electric vehicles technologies.

Increasing integration of these technologies is expected to increase the flexibility of the electric system (Bediako et al., 2014). Further, PV has one of the highest returns among other technologies without even considering the impact of policy incentives on distributed generation technologies (Vahl et al., 2013). Existing research has shown that residential electricity demand profile will change with increasing growth in distributed generation technologies (Veldman et al., 2013; Darghouth et al., 2014) while the government continues to subsidize cleaner electricity generation. Studies in this literature focus primarily on the effectiveness of the incentives for residential solar development and the impact of distributed generation on the grid. Current research has placed much less emphasis on the impact of solar integration on the utilities, which are still responsible for the transmission and distribution component of electric power to retail customers.

In this chapter, I explore the implications of the integration of distributed generation on electricity demand at the residential sector and consider distributed generation as an endogenous factor that influences residential electricity demand. This chapter extends the previous work on residential electricity demand by including on-site generation into the residential demand analysis and estimating price-responsiveness of the residential customers with increasing residential PV penetration. I also analyze the impact of the state policies (i.e., state NEM policy, state regulatory status) on residential PV capacity additions. Finally, using the estimation results, I project future electricity sales to the residential sector considering various future PV penetration scenarios. This projection is potentially useful for utilities in their resource planning and rate making processes as they formally incorporate the expected reduction in residential electricity demand due to increased penetration of distributed generation. Utilities may also benefit from this analysis in terms of understanding the implications of different levels of PV penetrations for their revenues and financial viability.

3.1.1 Policy Background

The U.S. share of solar generation has grown substantially with a 41% growth rate over the last year and has currently reached the total capacity of 17.5GW in the United States (SEIA, 2014). Solar installations have increased mostly due to the decline in the PV costs and state and federal incentives. The federal Solar Investment Tax Credits (SITC) program provides credits for 30 percent of the qualified investment and installation costs for the residential taxpayer who owns solar panels (DSIRE 2014). The SITC policy has been in effect since 2006 and is set to expire in 2016. Sener and Fthenakis (2014) note that solar tax credits have played an important role in the growth in solar investments in the US. Some states have formed Solar Renewable Energy Certificate (SREC) markets as an important feature of the Renewable Portfolio Standards, where electricity generated from PV can be traded separately from electricity as environmental attributes of renewable energy generated. A facility with 10kW capacity is able to generate approximately 12 SRECs annually (SRECTrade, 2014).

Another state program is Net Energy Metering (NEM), in which customers are given the option to pay only for the electricity that the customer purchases from the utility and allows the solar electricity generated on-site behind the retail meter to be used by the household or to be sold to the grid (SEIA, 2014a). Customers are billed for their net energy purchase from the utility and, in some cases, negative net balances can be carried forward to the next month's bill (Arnette, 2013; APPA, 2013). States vary considerably in the applications and regulations of their NEM policies and states may limit their generation capacity, eligible fuel type and total load for net metering (APPA, 2013).

State regulatory status on retail competition may also indirectly influence the rate of residential PV integration. Restructured states are states that offer full retail competition, so that customers can choose to buy power from alternative electricity suppliers. In un-restructured states, customers buy power from their local utility and their electricity rates are set by the Public

Utility Commissions (PUCs). One could argue that a competitive market environment is more conducive to new distributed energy technologies to enter the market compared to a monopolized vertically integrated electricity market. Some studies have indeed shown that the adoption of rooftop solar is stimulated more in restructured states compared to the un-restructured states (Morse, 1997; Spratley, 1998; Martionot et al., 2005; Cai et al., 2013). However, retail competition may actually discourage customers from adopting distributed generation because customers in restructured states are able to choose the least expensive electricity provider. Investing in distributed generation may not then be a cost-effective option. Between 2000 and 2012, restructured states had higher electricity prices than did un-restructured states (EIA, 2014d). See Appendix Figure 3.3. One then could argue that higher electricity prices may encourage residential customers to invest in rooftop solar, which allows these customers to generate their own electricity and reduce electricity purchases from the utility.

3.2 Methods

In this section, I provide a detailed explanation of the empirical model specification, including the justification for each of the variables included in the regression and the data used in the empirical analysis.

3.2.1 Empirical Model Specification

Most demand analyses of electricity consumption describes residential demand for an average customer as a function of electricity price, price of natural gas as a substitute for electricity, and demographic characteristics of the residential customers. Building on the underlying demand theory, I include capacity additions in residential distributed generation per customer (i.e., solar rooftop PV) into the residential electricity demand function. Below, I describe the system of equations and provide the rationale for the specification of the equations. . I then discuss which variables are endogenous and exogenous along with my estimation strategy

In the first equation, residential solar capacity installations per customer ($\mathrm{lnPV}_{t,s}$) is estimated as a function of state policies, the state's solar energy resource, residential electricity price and cost of rooftop solar. I normalize the residential solar capacity installations using the total number of residential customers in a given state. First, I include the state policies that incentivize solar for the residential sector. One of the most comprehensive state level policy variables that encompasses various components of distributed generation (i.e., the capacity, eligibility, policy and metering issues) is the NEM policy. As an effectiveness measure of the NEM policy, each state is assigned a grade (i.e. grades A through F, where A is the highest grade) every year based on the state solar integration policy applications. This NEM Grade ($\mathrm{NEMGrade}_{t,s}$) is calculated by considering the capacity, eligibility, policy and metering issues (Freeing the Grid, 2014). More specifically, the index includes the largest system allowed on net metering, total program limits, metering provisions, eligible technologies and customers, renewable electricity credits ownership and third party financing (i.e. leasing). State NEM grades show reasonable variation; some states have improved their grades (e.g., OH, WA) while some states have fallen behind over time (e.g., FL, MI). I provide a summary table about the calculation of the NEM grade in Appendix Table 3.1. I expect that the states with higher NEM grades are associated with higher residential solar penetration. Second, another state policy included to predict the PV capacity installations per customer is the state regulatory status on retail competition ($\mathrm{Restructured}_s$). Although the impact of state regulatory status is ambiguous, I expect that the states with restructured electricity markets would have higher solar penetration. Third, I include the residential price of electricity ($\mathrm{lnP}^{e}_{t,s}$) as an explanatory variable. I expect that the residential solar penetration is likely to be higher when there are higher residential electricity prices. This could be explained by the idea that customers facing higher electricity prices have a greater incentive to generate their own electricity by adopting rooftop solar.

I include the monthly horizontal solar radiation ($\mathrm{lnSolarRad}_{t,s}$) as an explanatory variable for rooftop solar installations. I expect that the states with higher solar radiation have higher PV penetration per customer. I also consider the monthly variation of the cost per Watt of PV installations across the states and this ratio includes the average installation costs ($\mathrm{lnAvrCostPV}_{t,s}$) before tax incentives or cash rebates applied for solar PV for each state. I expect higher PV capacity installations with the lower costs of solar PV installations. I also include time dummies of month (D_m^{month}), and year (D_y^{year}). Finally, some of the states in the sample (AZ, CA, CO, NJ, NV, PA, and WA) are categorized as early adopters because these states have longer history of PV capacity installations in the residential sector than the rest of the states. I expect that early adopting states have higher PV penetration per customer than later adopting states. Electricity price is the dependent variable in the second equation. The Public Utility Commission (PUC) is the public entity that sets the final retail rate for the residential sector and they set prices based on the marginal cost of electricity generation. I use the share of coal in the total generation mix ($\mathrm{CoalShare}_{t,s}$) and lagged electricity price ($\mathrm{lnP}_{t-1,s}^{e}$) as explanatory variables. Finally, I include the predicted residential solar installations ($\mathbf{lnPV}_{\mathbf{t,s}}^{*}$) and expect that, with higher solar capacity installation per customer, the price of electricity will increase due to the lower electricity sales from the utility. Because the utility will meet its revenue requirement with lower sales, the electricity price needs to increase.

The third equation explains the quantity of electricity demanded with the quantity of electricity consumed as the dependent variable. I estimate the residential electricity demand including the predicted values of residential electricity price ($\mathbf{lnP}_{\mathbf{t,s}}^{*\mathbf{e}}$) and the predicted residential solar installations ($\mathbf{lnPV}_{\mathbf{t,s}}^{*}$). I expect to find that the price of elasticity of electricity demand is negative for the residential customers. PV elasticity of electricity demand is also expected to be negative because with more solar capacity installations in the residential sector, more residential customers generate their own electricity and the share of electricity provided from the utilities should decrease. Since outside temperature affects the electricity demand in the residential sector, I also include monthly average temperature in each state. I expect to find a positive relationship between monthly temperatures ($\mathrm{lnTemp}_{t,s}$) and electricity demand. For example, residential electricity demand increases with higher outside temperatures during summer when residential customers extensively use their air conditioning. I include the natural gas price ($\mathrm{lnP}_{t,s}^{ng}$) as a substitute for electricity. A substantial number of residential customers use gas for heating their homes thus, when natural gas becomes an expensive energy source, residential electricity demand increases.

I include socioeconomic variables such as monthly disposable income for each state. Households with higher disposable income may use more electricity because they often own various electric appliances (TV, dishwasher, washer and dryer) that consume electricity. On the other hand, they may have more energy efficient appliances and homes and this may dampen their electricity consumption. The net effect can be determined empirically. Finally, I control for the electricity demand reduction due to energy efficiency programs, which have had an important impact on the electricity demand management at the residential sector. Thus, I include states' energy efficiency scores as reported by the American Council for Energy Efficient Economy (ACEEE) in order to control for the state performance on energy management. States with higher energy efficiency score ($\mathrm{lnACEEEScore}_s$) are expected to have lower electricity demand per residential customer. The system of equations for residential electricity demand is provided here, and Table 3.1 summarizes the description of the variables used in the empirical analysis.

$$\ln PV_{t,s} = \alpha_0 + \alpha_1 NEMgrade_{t,s} + \alpha_2 Restructured_s + \alpha_3 P^e_{t,s} + \alpha_4 \ln SolarRad_{t,s} + \alpha_4 \ln AvrCostPV_{t,s} + \alpha_5 EarlyPVAdopters + D^{year}_y + D^{month}_m + \varepsilon_{1,t,s} \quad (3.1)$$

$$\ln P^e_{t,s} = \beta_0 + \beta_1 CoalShare_{t,s} + \beta_2 \ln P^e_{t-1,s} + \boldsymbol{\beta_3 \ln PV^*_{t,s}} + \beta_4 EarlyPVAdopters + D^{year}_y + D^{month}_m + \varepsilon_{2,t,s} \quad (3.2)$$

$$E_{t,s} = \theta_0 + \boldsymbol{\theta_1 \ln P^{e*}_{t,s}} + \theta_2 \boldsymbol{\ln PV^*_{t,s}} + \theta_3 \ln P^{ng}_{t,s} + \theta_4 \ln Temp_{t,s} + \theta_5 Restructured_s + \theta_6 \ln Income_{t,s} + \theta_7 \ln ACEEEScore_s + \theta_8 EarlyPVAdopters + D^{year}_y + D^{month}_m + \varepsilon_{3,t,s} \quad (3.3)$$

The endogenous variables in this system of equations are residential solar capacity installations ($\ln PV_{t,s}$), residential retail electricity price ($\ln P^e_{t,s}$) and residential electricity demand per customer ($\ln E_{t,s}$). Residential solar PV capacity and residential electricity demand depends in part on the residential retail electricity price ($\ln P^e_{t,s}$). Because of this endogeneity, the price equation is identified using instrumental variables of share of coal[13] ($CoalShare_{t,s}$) and lagged electricity price ($\ln P^e_{t-1,s}$). Coal is often used as base load generation and it is a relatively cheaper fuel than natural gas or diesel oil. An increase in the share of coal in electricity generation would reduce electricity prices due to using relatively cheaper input for generation, which would ultimately increase residential electricity demanded. Coal share in the monthly generation mix can only affect electricity demanded through the price of electricity, which is only determined by the shift in electricity supply. I expect to find a strong positive relationship between the electricity price and the monthly lagged electricity price due to stability of price setting by the PUC.

[13] Natural gas share could be good instrument but it is not included into the analysis because of high correlation (See Appendix Figure 3.2)

Table 3. 1: Description of the Variables

Variable	Description	Unit	Notation
Solar Capacity	PV Capacity Installations per Residential Customer	MW/Customer	$\mathrm{PV}_{t,s}$
Electricity Price	Real Average Residential Electricity Price (All-in)	Cents/kWh	$\mathrm{P}^{e}_{t,s}$
Electricity Demand	Real Monthly Residential Electricity Sales per Customer	MWh/Customer	$\mathrm{E}_{t,s}$
Solar Radiation	Aggregate Horizontal Solar Radiation by State	$\mathrm{Wh/m^2}$	$\mathrm{SolarRad}_{t,s}$
NEM Grade	Net Energy Metering Grade by State (=1 if grade is A; otherwise grade is 0)	Binary variable	$\mathrm{NEMgrade}_{t,s}$
Cost of Solar	Monthly per watt cost of PV by state before incentives applied (max 5kW)	$/Watt	$\mathrm{AvrCostPV}_{t,s}$
Restructured	State Regulatory Status	1 if restructured; 2 if suspended; 0 otherwise;	$\mathrm{Restructured}_{s}$
Coal Share	Share of Coal in Electricity Generation (%)	Amount of Coal/Total Fuel	$\mathrm{CoalShare}_{t,s}$
NG Price	Real Residential Natural Gas Price	$\$/ft^3$	$\mathrm{P}^{ng}_{t,s}$
Temperature	Monthly Average Temperature	°F	$\mathrm{Temp}_{t,s}$
ACEEE Score	The state energy efficiency ranking	State rankings range from 1 to 50. Higher score indicates better energy efficiency	ACEEEScore
Disposable Income	Monthly Disposable Income per Customer by State	Levels	$\mathrm{Income}_{s,t}$

I use three stage least squares (3SLS) method to estimate the system of equations. The model specification is also consistent with the assumptions that the error term is not correlated with the exogenous variables in the model $\mathrm{Cov}(\varepsilon_{i,t,s}|X_{i,s,t}) = 0$, where $X_{s,t}$ represents the exogenous variables on the right hand-side of each equation, i represents the number of equations ($i = 1,2,3$), s represents the states and t represents each month ($t = 1 \ldots T$), taking into account cross-equation correlation of error. The instrumental variables $Z_{s,t}$ are also highly correlated with the endogenous variable, industrial electricity price ($\ln P_{s,t}$), and uncorrelated with the error term $\varepsilon_{t,s}$ (Cov ($P_{s,t}, z_{s,t}) \neq 0$ and Cov ($\varepsilon_{s,t}, z_{s,t}) = 0$) (Wooldridge 2011, 247). I test these assumptions in the Results section. In Table 3.2, I summarize the expected sign from each independent variable and my hypotheses for the stated expected impacts.

3.3 Data

Empirical analysis focuses on the period between 2008 and 2012 because of the substantial increase in residential PV capacity installation has been within this period (See Appendix Figure 3.2). There are 23 states with data on residential PV penetration[14]. Ten of them are restructured, eight are un-restructured and five have suspended restructuring. Restructured states included in the analysis are Texas, Illinois, Oregon, Ohio, Pennsylvania, New York, Maryland, Delaware, New Jersey and Massachusetts. Un-restructured states included in the analysis are Arizona, California, Colorado, Florida, Indiana, North Carolina, New Mexico, Nevada, Utah, Virginia, Vermont and Washington (EIA, 2010)[15]. Nevada has the highest and Georgia has the lowest average PV capacity installations per customer. The average quantity of annual electricity sales per customer is approximately 954 kWh and the average residential electricity price is

[14] States in the sample: AZ, CA, CO, DE, FL, GA, IL, IN, MA,MD, NC, NJ, NM, NV, NY, OH, OR, PA, TX, UT, VT, WA.

[15] Other restructured states in the US (Michigan, Connecticut, Maine and New Hampshire) are eliminated from the analysis because of not having sufficient data points on the residential PV capacity installations.

Table 3. 2: Hypotheses on the Coefficient Estimates

Estimated Equation	Variable	Expected Sign	Hypothesis
Equation 1 Solar Capacity	Electricity Price	+	Increase in electricity price increases PV penetration
	Solar Radiation	+	With higher solar radiation, PV penetration increases
	NEM Grade	+	States with higher NEM grade have higher PV penetration
	Cost of Solar	-	With lower solar PV costs, PV capacity installations increases
	Restructured	+	Restructured states have higher PV penetration
Equation 2 Electricity Price	Coal Share	-	Increase in share of coal in the generation mix decreases price of electricity
	Lagged Electricity Price	+	Increase in previous month's price increases price of electricity
	Solar Capacity	-	Increase in residential PV capacity installations decreases price of electricity
Equation 3 Electricity Demand	Electricity Price	-	Increase in electricity price decreases electricity demanded
	Solar Capacity	-	Increase in PV penetration decreases electricity demand
	NG Price	+	Increase in natural gas prices increases electricity demand (substitution effect)
	Temperature	+	With higher temperatures, electricity demand decreases
	ACEEE Score	-	With higher energy efficiency score, residential demand decreases
	Disposable Income	+	With higher disposable income, residential electricity demand increases

12cents/kWh. The highest monthly average quantity of residential electricity sales per customer is in North Carolina (1,1592kWh/customer), where the residential electricity price is 11.8 cents/kWh. Restructured states have higher average monthly electricity prices. Further, all restructured states, with the exception of Texas, have NEM grades higher than “C”. I compare the monthly average residential electricity prices for restructured and un-restructured states in Appendix Figure 3.3 and Appendix Table 3.3 lists states and their NEM grades.

I obtain monthly residential electricity sales and residential PV capacity installations data from the Energy Information Administration (EIA) monthly electric power database, solar radiation data from National Renewable Energy Laboratory’s Solar Database, Net Energy Metering (NEM) grades from the Solar Energy Industry Association, and temperature data from Midwest Regional Climate Center. Residential electricity price is the average all-in electricity price offered by the utilities to residential customers in each state and residential electricity sales is the average monthly electricity consumption per residential customer in each state. Utilities report the monthly PV capacity installations for the residential sector and I use the aggregated monthly capacity by state between 2008 and 2012. State regulatory status data is again obtained from the EIA. NREL Solar data provides the monthly aggregate horizontal solar radiation for multiple stations in each state between 1990 and 2010. (See Appendix Table 3.4 for the list of data sources) Since this study goes through 2012, I applied linear extrapolation[16] for the years 2011 and 2012. I aggregate the solar radiation for each month by state. The share of coal in electricity generation mix and the residential natural gas prices are also obtained from the EIA. I obtain the cost of PV data from the Open PV project by National Renewable Energy Laboratory (NREL), in which the solar rooftop installers report the total number of installations, cost per Watt ($/Watt) and the capacity of the technology installed (MW). I only include the residential

[16] I use “Ipolate” command with epolate option in Stata to conduct the linear extrapolation. I have sufficient historical data points to do the extrapolation.

PV installed up to 5kW into the regression, which is approximately the maximum of residential capacity installed in the US. Finally, I used GDP deflator by each state to eliminate the inflation over time on electricity price and natural gas prices to correct for inflation. Table 3.3 shows the summary statistics.

Table 3. 3: Descriptive Statistics

				Quantiles			
Variable	**Mean**	**S.D.**	**Min**	**0.25**	**Median**	**0.75**	**Max**
Solar Capacity (MW/Customer)	36.36	71.1	0	2.41	12.5	37.35	635.22
Electricity Price (cents/kWh)	11.68	5.08	6.17	8.9	10.11	12.39	42.63
Electricity Demand (MWh/Customer)	1.48	5.32	0.45	0.67	0.85	1.12	71.18
Solar Radiation (Wh/m^2)	71,690	69,843	2,972	30,131	55,400	84,891	550,000
NEM Grade	0.22	0.42	0	0	0	0	1
Cost of Solar ($/Watt)	7.33	2.44	0	6	7.15	8.39	51.99
Restructured (binary)	0.43	0.5	0	0	0	1	1
Coal Share (%)	0.28	0.31	0	0.03	0.15	0.48	1
NG Price ($\$/ft^3$)	14.76	6.59	6.53	10.4	13.6	17.07	60.72
Temperature (°F)	53.76	16.38	10.9	40.7	54.3	67.2	88.2
ACEEE Score (levels)	24.45	9.33	3	18.5	22	30	45.5
Disposable Income (levels)	18.8	1.04	16.05	17.92	18.83	19.61	21.44

3.4 Results

3.4.1 Estimation Findings

In the first equation, residential solar capacity installations equation, I find that residential PV capacity installations are about 0.07% higher with higher NEM grades (i.e., grade A relative to B). Compared to the un-restructured states, restructured states have about 3.5% higher residential

PV capacity installations. I also find that 1% increase in the residential electricity price is associated with about 0.11% increase in residential PV capacity installations. I find that with 1% higher horizontal solar radiation increases residential PV capacity installations per customer by about 1.13%. With a percent lower total cost of PV installations before the financial incentives increases the residential PV capacity installations by about 0.14%. State regulatory status (i.e. restructured vs. un-restructured) and solar source variables are statistically significant at 1% significance level and have the expected coefficient signs.

All of the coefficients of the year dummies are positive and statistically significant. It means that compared to year 2008, residential PV capacity installations have increased over time. For example, capacity installations are about 0.7% higher in 2009 and 3.7% higher in 2012 compared to year 2008. Compared to January, PV capacity additions are significantly higher during September through December. Predicted coefficients for month dummies are all positive but statistically not significant except for the months September through December.

In the second equation, the residential electricity price equation, I find that the residential customers respond to the price changes in the previous month's bill. A 1% increase in electricity price in the previous month increases the expectations on the current electricity price by 0.94%. Further, a 1% increase in share of coal in the generation mix, decreases the electricity price by about 0.5%. These instruments are statistically significant, which is also an indicator of an appropriate instrument for the price equation. Also, a 1% in the predicted residential PV capacity installations per customer increases the electricity price by about 0.04% and it is statistically significant. Residential electricity prices (i.e. real prices) are lower over time compared to the prices in 2008. Residential price is about 0.06% lower in 2009; 0.15% lower in 2010; significantly 0.27% lower in 2011 and 0.28% lower 2012 compared to the prices in 2008. The residential electricity price is higher during December, February and March compared to the residential prices in January but the prices are lower in other months compared to January. However, monthly dummies are statistically insignificant.

In the third equation, the residential electricity demand equation, I find that a 1% increase in electricity price per customer is associated with about 0.15% decrease in residential electricity demanded per customer. Further, a 1% increase in residential PV capacity installations per customer is associated with about 0.03% decrease in residential electricity demand per customer. Also, an increase in the natural gas price, the substitute fuel for electricity, increases electricity demand by 0.2%. Residential electricity demand per customer increases by about 0.4% if the outside temperature increases by one percent. With 1% higher disposable income, electricity demand per customer is 0.11% higher. States with higher ACEEE energy efficiency score have lower residential electricity demand per customer by about 0.14% but this impact is not statistically significant. Residential electricity demand per customer has slightly increased over time compared to the residential demand per customer in 2008. Residential demand per customer is about 0.07% higher in 2009; 0.15% higher in 2010; 0.20% higher in 2011 and 0.14% higher in 2012 compared to the electricity demand per customer in 2008, and the increase relative to year 2008 is statistically significant. Residential electricity demand per customer in each month is significantly lower compared to residential electricity demand per customer on January, which is typically the coldest month when the demand for electricity is the highest compared to the other months. In Table 3.4, I present the summary of the regression statistics and the regression results of the Three Stage Least Squares estimations.

Table 3. 4: 3SLS Monthly Regression Summary and Regression Results

Equation	Observations	Parameters	RMSE	R-square	F-Stat	P-Val
1st Stage	523	27	0.817738	0.8059	76.28	0.0001
2nd Stage	523	25	0.222399	0.9422	324.8	0.0001
3rd Stage	523	28	0.193129	0.6556	34.34	0.0001

Equation 1 Solar Capacity	**Estimation**	**T-stat**	**Equation 2 Electricity Price**	**Estimation**	**T-stat**	**Equation 3 Electricity Demand**	**Estimation**	**T-stat**
Solar Radiation	1.131***	-10.73	Lagged Electricity Price	0.939***	-47.31	Electricity Price	-0.146***	-4.35
Cost of Solar	-0.136	-0.56	Coal Share	-0.467***	-6.09	Solar Capacity	-0.032	-1.61
NEM Grade	0.067	-1.59	Solar Capacity	0.040**	-2.46	NG price	0.237***	-4.78
Restructured	1.085***	-7.16	Constant	0.231	-0.7	Temperature	0.370***	-4.68
Electricity Price	0.109	-1.32	year2009	-0.055	-1.38	ACEEE Score	-0.144***	-5.09
Constant	-27.635***	-16.94	year2010	-0.151***	-3.33	Disposable Income	0.109**	-2.32
year2009	0.691***	-4.84	year2011	-0.270***	-4.81	Constant	-2.475***	-4.74
year2010	1.615***	-11.51	year2012	-0.278***	-3.8	year2009	0.072*	-1.94
year2011	2.635***	-17.56	month2	0.01	-0.21	year2010	0.154***	-3.25
year2012	3.707***	-22.78	month3	-0.003	-0.05	year2011	0.201***	-3.2
month2	-0.301*	-1.68	month4	-0.011	-0.23	year2012	0.144*	-1.79
month3	-0.653***	-3.42	month5	-0.029	-0.6	month2	-0.167***	-3.95
month4	-0.787***	-4.09	month6	-0.043	-0.88	month3	-0.328***	-6.79
month5	-0.933***	-4.63	month7	-0.036	-0.74	month4	-0.507***	-9.59
month6	-0.865***	-4.25	month8	-0.038	-0.8	month5	-0.508***	-8.45
month7	-0.790***	-3.94	month9	-0.032	-0.64	month6	-0.359***	-5.4
month8	-0.588***	-3.05	month10	-0.034	-0.7	month7	-0.147**	-2.07
month9	-0.281	-1.48	month11	-0.03	-0.61	month8	-0.184***	-2.66
month10	0.308*	-1.74	month12	0.011	-0.23	month9	-0.312***	-4.83
month11	0.522***	-2.92	dumAZ	-0.077	-1.43	month10	-0.436***	-8.05
month12	0.998***	-5.68	dumCA	-0.082**	-2	month11	-0.398***	-8.43
dumAZ	0.492**	-2.18	dumCO	0.045	-0.79	month12	-0.062	-1.45
dumCA	-1.980***	-5.85	dumNJ	-0.156***	-3.06	dumAZ	0.296***	-5.9
dumCO	2.562***	-12.27	dumNV	-0.182**	-2.37	dumCA	-0.128**	-2.09
dumNJ	2.495***	-13.09	dumPA	0.039	-1.02	dumCO	0.119**	-1.99
dumNV	2.505***	-11.91	dumWA	0.2	-0.87	dumNJ	-0.254***	-5.07
dumPA	-0.680***	-4.46				dumNV	0.282***	-3.91
dumWA	-1.813**	-2.13				dumPA	0.076**	-2.04
						dumWA	0.624***	-3.09

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Using the output from the regression analysis, I can compute the price elasticity of residential electricity demand and PV elasticity residential electricity demand. Price elasticity of electricity demand can be defined as follows:

$$\varphi = \frac{\delta \text{ElecSalesperCustomer}}{\delta \text{RealPrice}} \cdot \frac{\text{RealPrice}}{\text{ElecSalesperCustomer}}.$$

This model specification is in log-log form and I can directly obtain φ from the third stage of the estimation $\varphi = \frac{\delta \text{lnElecSalesperCustomer}}{\delta \text{lnRealPrice}}$. The estimated price elasticity of demand is -0.146 and it is statistically significant at the 1% significance level. This estimate is consistent with the electricity price estimates based on the previous literature. See Appendix Table 3.2. Residential PV elasticity of demand, responsiveness of the residential demand to PV penetration, can also be directly obtained from the third-stage. Residential PV elasticity of demand can be computed as

$$\rho = \frac{\delta \text{ElecSalesperCustomer}}{\delta \text{TotalPVcapacityperCustomer}} \cdot \frac{\text{TotalPVcapacityperCustomer}}{\text{ElecSalesperCustomer}}.$$

Similarly, I can directly obtain $\rho = \frac{\delta \text{lnElecSalesperCustomer}}{\delta \text{lnTotalPVcapacityperCustomer}}$ from the third-stage of the regression. The parameter is not statistically significant but it is at 11% level.

These elasticity values indicate that 1% increase in the residential electricity price, electricity sales per customer decreases by 0.146% and an additional for 1% increase in residential solar PV capacity installations per customer, electricity sales per customer decreases by about 0.03%. I present the elasticity estimates in Table 3.5. All of the standard errors in the regression results and standards errors for the elasticity estimations are bootstrapped.

Table 3. 5: Elasticity Estimates

Elasticity	Coeff.	Std.Err	z	P>z	Confidence Interval	
Price Elasticity of Demand φ	-0.15	0.03	-4.35	0.0001	-0.211	-0.08
PV elasticity of Demand ρ	-0.03	0.03	-1.61	0.107	-0.070	0.007

Finally, I test whether there is correlation among the error terms in the simultaneous equations and there is no significant evidence of high correlation among the error terms within the system. Rank and order conditions in the system are met and the system of equations is correctly identified. I also test the validity of the instruments: 1) included instruments are independent of the error term and 2) included instruments are sufficiently correlated with the endogenous variables. I check the goodness-of-fit test for the second stage in order to check the whether the excluded instruments are sufficiently correlated with the endogenous variable. The F statistics results are statistically significant (F-test statistic 324.8; p-value 0.0001) indicating that the equation is not weakly identified. Since all of these test statistics are valid under the i.i.d and homoscedasticity assumption, I check for the overall system heteroscedasticity testing the null hypothesis of no overall heteroscedasticity and the LR test statistics fail to reject the null hypothesis (LR Test 9.2932; p-value 0.0256). I also check the diagonal covariance matrix using Breusch-Pagan Lagrange Multiplier statistic (Shehata, 2011; Shehata, 2012) which shows that 3SLS is a better specification than OLS. Thus, I reject the null hypothesis of independent equation in simultaneous equation system (LM Test statistic 8.55905, p-value 0.0221).

3.4.2 Application of the Empirical Findings

I use the estimated elasticity values and project the share of the utility electricity sales reduction of the total sales to residential sector between 2013 and 2020. I assume that 5%, 10%, 15%, 20% and 25% of the residential customers have rooftop PV by 2020. I conduct a simulation for a representative state, where there has been considerable amount of residential PV penetration between 2008 and 2012 (SEIA 2014b). The average residential PV capacity installed by 86MW and the average electricity price is 11cents/kWh between 2008 and 2012. Further, the average monthly residential electricity consumption per customer is approximately 1000kWh. The representative state has a successful Net Energy Metering policy. In other words, it the highest NEM grade of "A" in 2012. In Table 3.6, I provide summary statistics for the representative state.

Table 3. 6: Summary Statistics for the Representative State

	Mean	S.D.	Min	0.25	Median	0.75	Max
Solar Capacity (MW/ Customer)	86	157	4	9	9	44	635
Electricity Price (cents/kWh)	11	0	10	11	11	11	12
Residential Sales (MWh/Customer)	1.1	0.4	0.7	0.8	1.0	1.4	1.8

The simulation procedure I conducted is as follows:

- I first obtain the total system peak demand (MW) and number of residential customers for the representative state between 2008 and 2012 from Energy Information Administration (EIA). Assuming that approximately 30% of the total customers are residential customers, I calculate residential peak demand.
- I calculate the average annual growth in residential peak demand and project forward the peak demand through 2020 using the calculated growth rate and I calculate residential peak demand per customer by scaling the demand with the number of residential customers.

- Assuming a 5, 10, 15, 20 and 25 percent of number of residential customers with PV by 2020, I calculate the average annual growth rate to achieve these assumed projected residential PV penetration levels.
- I then apply the elasticity values along with the calculated annual PV penetration growth rates for each scenario. Based on the empirical analysis, I find that a percent increase in residential PV installations decreases electricity demand per customer by about 0.032%. For example, if the projected PV installations increase by 3%, projected residential electricity demand per customer are expected to diminish by about 0.096% (0.03*0.032).
- Finally, I multiply the projected residential demand per customer with the total number of customer to obtain the aggregate impact of the reduction in residential demand due to PV penetration under different penetration scenarios.

These projections show that electricity sales to the residential customer in the representative state decrease. For example, in a 25% residential PV penetration scenario by 2020, about 1.2% of the projected growth of the electricity sales to the residential customers will be taken over by rooftop solar. Figure 9 shows the share of the residential sales reduction in the total residential sales.

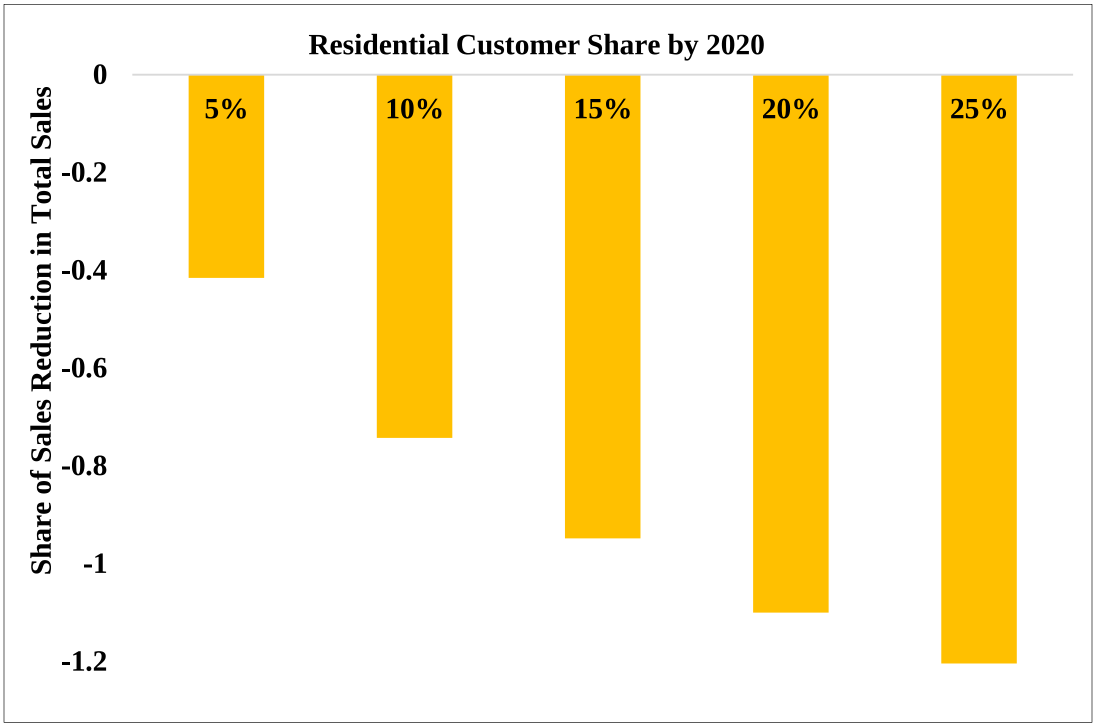

Figure 3. 1: Projected Electricity Sales per Customer

3.5 Discussion and Policy Implications

Distributed generation technologies used to be perceived as expensive and uncertain source of electricity. However, with the steep decrease in the distributed generation technology costs and the availability of various financing options and policy incentives, the penetration of these technologies have substantially increased over the past decade (Hyde and Komor, 2014; Burkhardt et al., 2015). Consumer-owned PV penetration has been currently one of the fastest growing distributed generation sources in the residential sector (Cai et al. 2013). In fact, a McKinsey study estimates that by 2020 the distributed PV capacity may reach 193 MW by 2020, representing 19 percent of the U.S. generating capacity projected by EIA in 2020. Therefore, it is essential to understand the impact of increased DG penetration on the electricity sales as it has direct consequences for the future of electric utility business model.

Growth of electricity demand has slowed in each decade since the 1950s, from 9.8% per year from 1949 to 1959 to only 0.7% per year since 2000. In the Annual Energy Outlook 2014

Reference Case, electricity demand growth remains relatively low (projected at 0.9% per year), as rising demand for electric services is offset by efficiency gains from new appliance standards and investments in energy-efficient equipment. The sales growth rate is expected to decline further with the increasing residential PV penetration due to falling solar panel prices, favorable net energy metering policies, and rising electricity prices. With more residential PV penetration, electricity demand of the residential customers decreases and is projected to decrease at increasing rates in the next decade. Although the application of Net Energy Metering (NEM) is different at each state including capacity limits, metering issues and eligible customers and technologies, these policies contribute to the growth in residential PV capacity installations. Also, expiration of the federal tax credits for wind will also make solar more attractive and cost-effective renewable energy resource (Arnette, 2013). Further, restructured states, where retail prices are higher compared to the un-restructured states, are predicted to have higher residential PV capacity installations. Thus, state retail competition is also an important driver of the distributed generation at the residential sector.

Increasing share of the solar generation by the residential customers have several benefits to the customers, to electric grid and to the environment. First, there are no emissions associated with producing energy from solar. Second, the marginal cost of producing solar is also zero, in addition to the rapidly decreasing investment costs (Brown and Bunyan, 2014). There are also additional benefits of increasing PV penetration such as demand response, although the empirical analysis does not directly consider the relationship between distributed generation and demand response.

Despite various benefits of increased residential solar PV penetration, increasing number of residential customers with distributed generation has increased the concerns of the utilities that serve to these customers (Costello and Hemphill, 2014). This is mainly because a higher penetration of residential sales implies lower sales for electric utilities, which still have to recover their revenue requirements to be able to sustain reliable and affordable service. Utilities in regions with high PV penetration. Utilities in regions with high PV penetration such as Arizona and California have already started to consider redesigning their rates (Jannson and Michaelfelder, 2008; Carson and Davis, 2014). For instance, Arizona's largest electric utility company, Arizona Public Service Company (APS) designed experimental net metering plans, which includes additional fixed charges, $0.70/kW for the residential rooftop owners. Similarly, PG&E, California's largest utility charges between $4-5/month to all residential customers, in addition to the fixed NEM fee for the residential rooftop PV owners (Carson and Davis, 2014). With increased fixed charges, or three part tariffs, the customers who choose to adopt residential PVs will pay their fair share of the costs imposed on the system.

The analysis in this essay can be used by utilities to simulate the sales impact of increased residential PV penetration in their service territories and understand the implications for their revenue requirements. Having projected the potential revenue scenarios, they can more readily plan for future investments, rate-design initiatives, integrated resources plans and other operational functions.

3.6 Conclusions

This essay empirically analyzes the impact of residential rooftop solar on residential electricity demand. The model includes system of equations and predicts residential electricity demand using three-stage least squares estimation method. In the first stage, I predict the residential PV capacity installations controlling for the state policies, state solar resource and market variables. In the second stage, I estimate residential electricity price using instrumental variables. In the third stage, I predict the residential electricity demand simultaneously estimating the system of equations. Using the estimation results, I compute the price elasticity of demand and residential

PV capacity installations of demand. This analysis concludes with projecting the utility sales to the residential customers with solar generation using the elasticity estimates.

I have several data limitations and this study could significantly be improved by overcoming these limitations. One of the major limitations is the sufficient data points on monthly residential PV capacity installations for several states. I had to exclude a number of states from the empirical analysis. Another data limitation is that I was not able to identify the variation across the states in terms of state performance on federal incentives. For example, I could not retrieve any time series data on the level of residential PV capacity installations incentivized by the federal credits at the state level. This could disaggregate the policies for residential PV penetration and quantify the impact of the federal subsidies on the residential PV penetration, in addition to the state policies.

4. Conclusions

The objective of this dissertation is to analyze the economics of renewable electricity generation from wind and solar and the adoption of demand response in the electricity markets.

First chapter includes solving a particular wind investment model considering the uncertainties about the future of the PTC policy and the stochastic REC prices. The solution of this optimization model includes finding a profitability threshold for investment in a small scale merchant wind development project. I find that the REC threshold is lower with the PTC policy. I also show that the investment decision is sensitive to the level of uncertainty about the PTC incentive and the REC prices. Higher uncertainty in the PTC policy increases the REC price threshold for the investment in wind energy. This chapter contributes to an understanding of how the uncertainties in these policies will impact future wind investments over the next 20 years.

Second chapter hypothesizes that there are regional differences in price-responsiveness for industrial sector both in retail and wholesale electricity markets in the MISO region. The empirical analysis employed in this chapter aims to create a discussion on the connection between the retail electricity market, in which industrial consumers often purchase electricity through relatively flat retail rates, and the wholesale electricity market, where market participants are able to change their electricity transactions based on real-time price changes. Price responsiveness is strongest in sub-regions where long-term industrial retail price-responsiveness is highest (i.e. Michigan and, to a lesser extend Minnesota). Results also suggest that generation and distribution utilities transacting at the wholesale level are able to respond in modest ways to real-time price changes, even without the demand-pull of a price-informed retail market.

In third chapter, residential electricity demand is estimated considering fast growing distributed generation resource, residential rooftop solar that affects demand for electricity at the residential sector, and ultimately affects utility revenues. The analysis in this chapter can be used by utilities to simulate the sales impact of increased residential PV penetration in their service territories and understand the implications for their revenue requirements. Having projected the potential revenue scenarios, utilities can more readily plan for future investments, rate-design initiatives, integrated resources plans and other operational functions.

In sum, this dissertation contributes to the understanding of the impact of policy on electricity generation from renewable resources such as wind and solar. It provides an understanding of the implications of industrial customer responsiveness in different states on the wholesale market and state-monitored demand response adoption across the MISO region. First chapter in this dissertation could be expanded study by looking at the impact of uncertainty in state and federal policy on wind energy investments in conjunction with the heterogeneity in wind turbines and employ empirical methods to demonstrate the impact of the uncertainty around the PTC on the historical investments in the US. Also, future research is needed to build improved understanding of industrial customers in different sectors and explore industrial price responsiveness and adoption of demand response across state regulatory and regional market governance environments. The empirical approach in second chapter could be considerably improved with more granular consumer-level data. Finally, future research may focus on the environmental implications on renewable electricity generation and the adoption of demand response.

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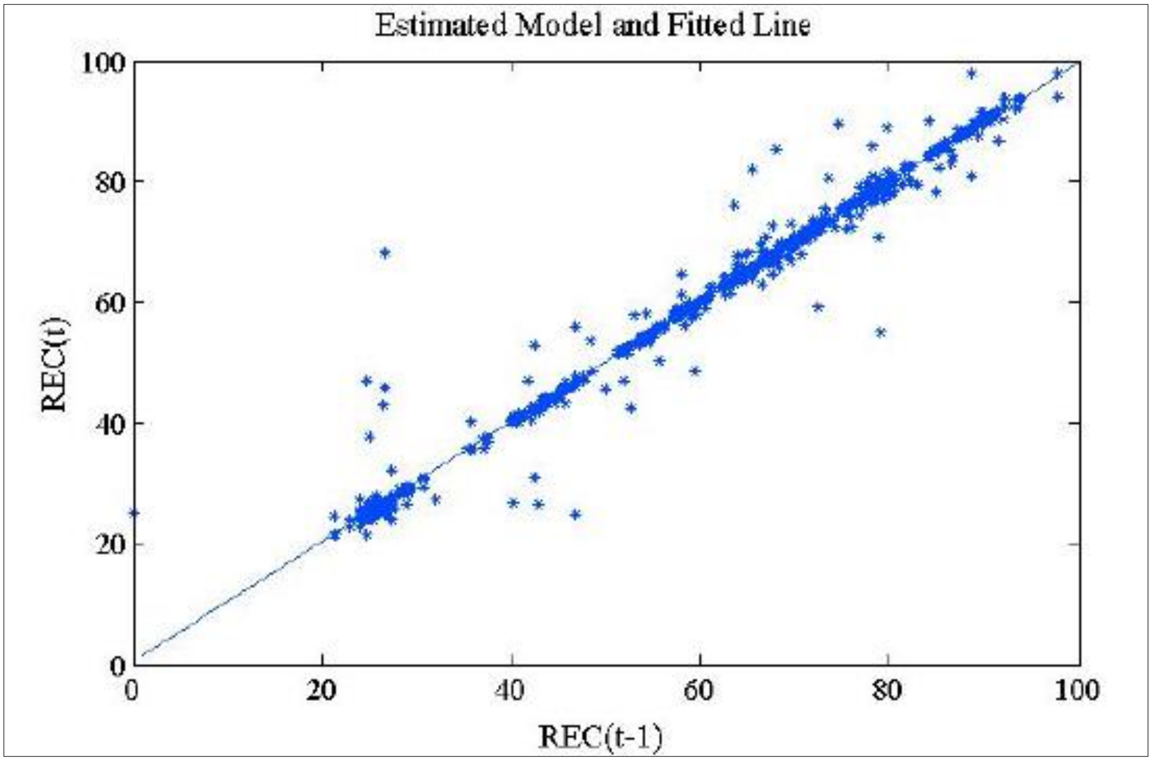
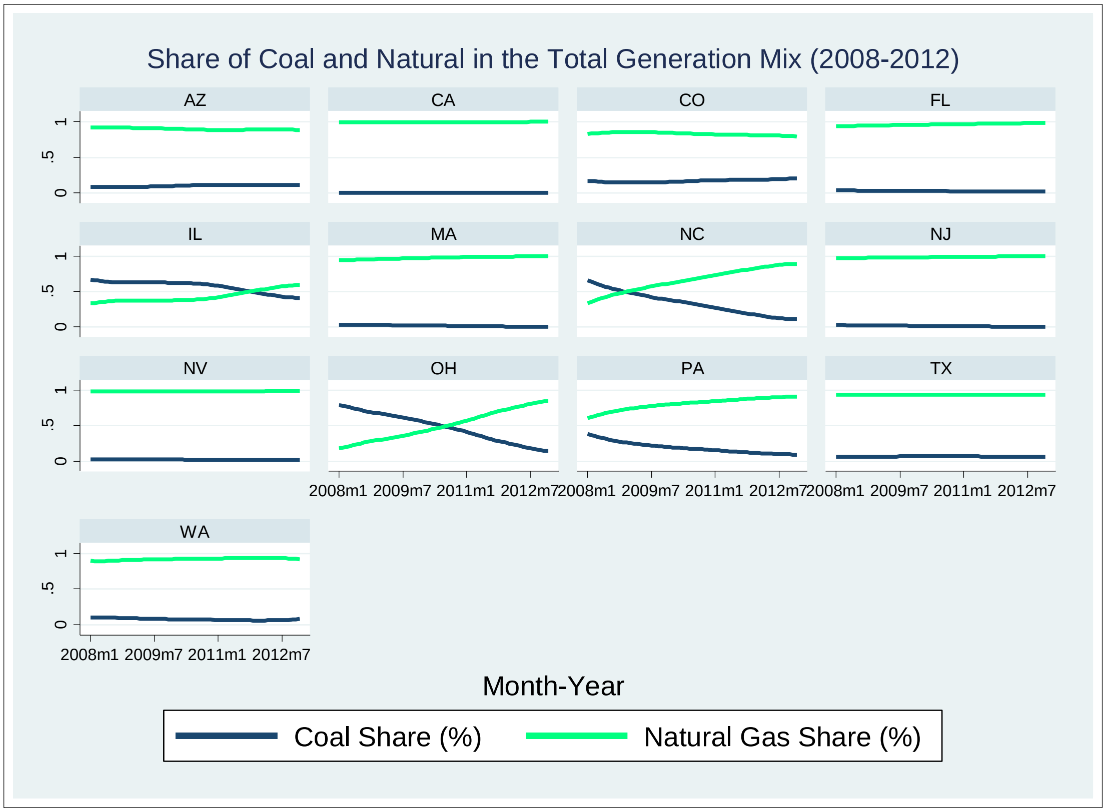
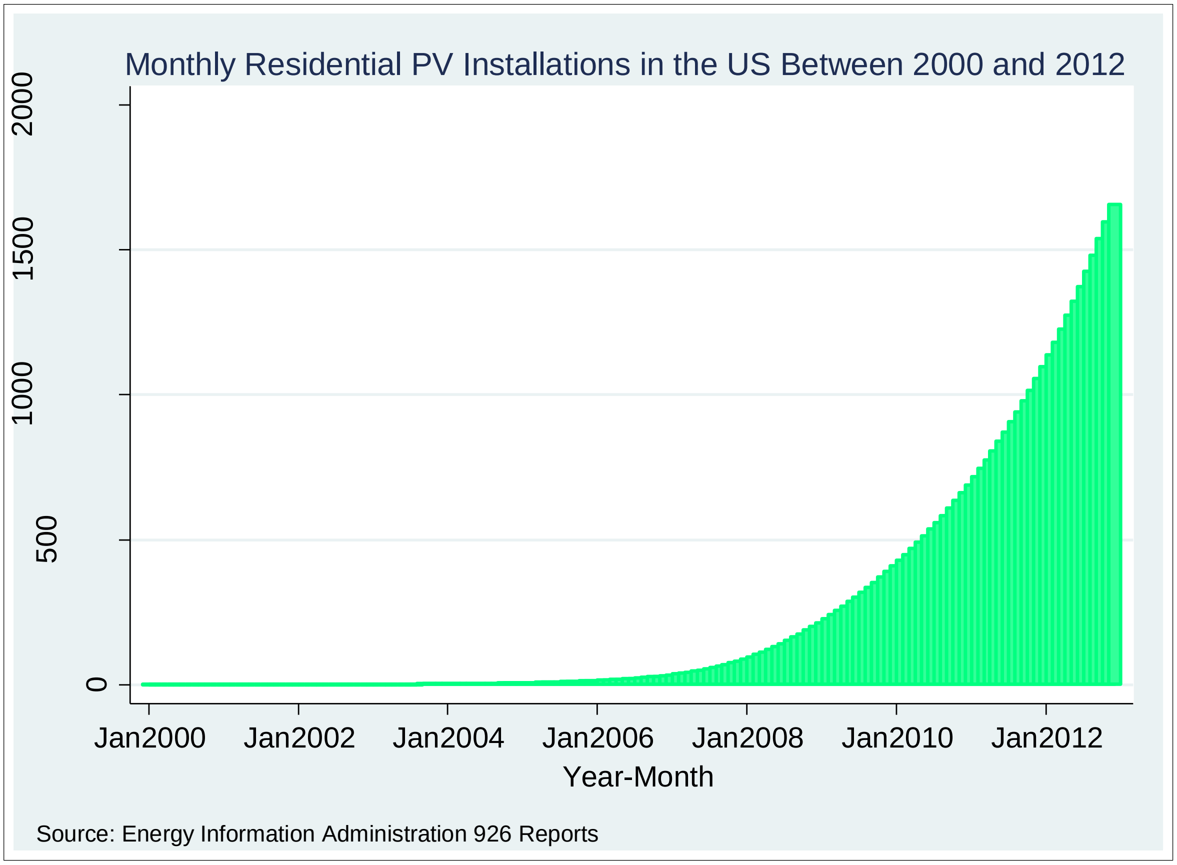
6. Appendix



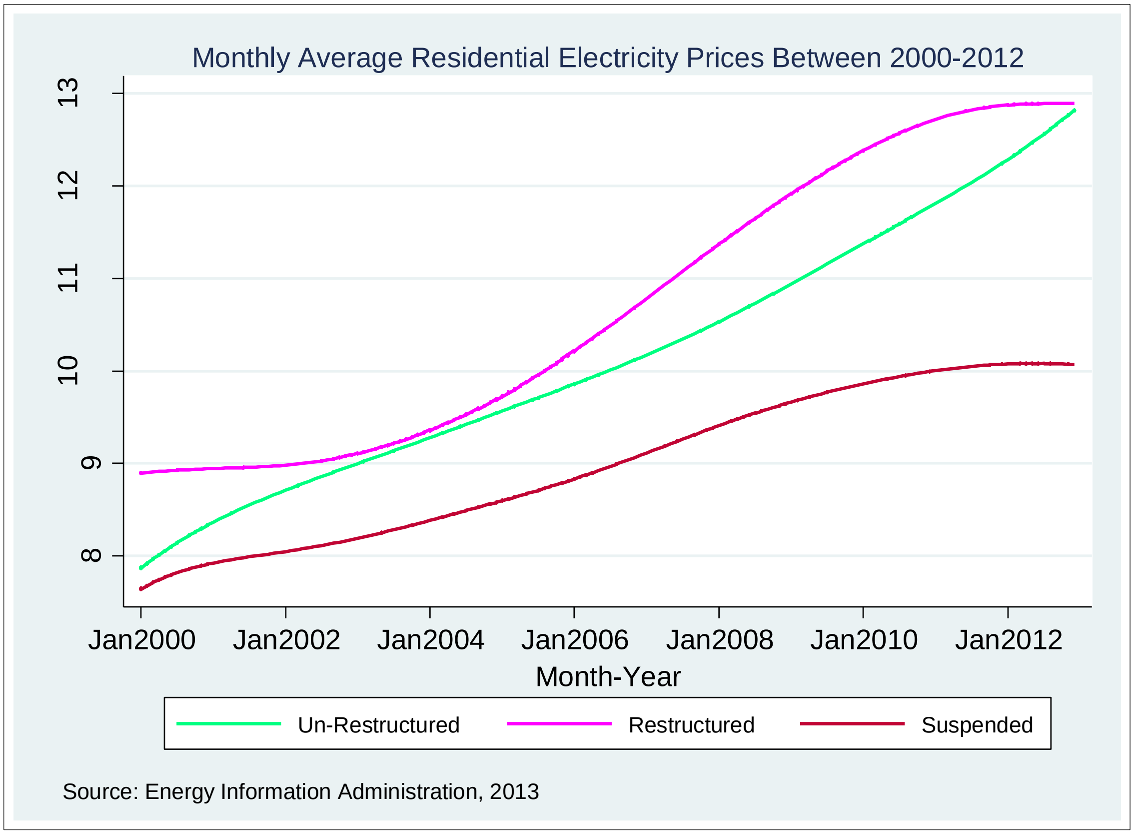
Appendix Figure 1. 1



Appendix Figure 3. 1: Share of Coal and Natural Gas in Total Generation Mix



Appendix Figure 3. 2: PV installations between 2008 and 2012



Appendix Figure 3. 3: Monthly Average Residential Electricity Prices

Appendix Table 1. 1: OLS Regression Output for Calibration

	REC Price
L.REC Price	0.994***
	(326.14)
Constant	0.3709*
	(1.91)
N	1562
R-sq	0.99

t statistics in parentheses
* p<0.1 ** p<0.05 *** p<0.01

Appendix Table 2. 1: Dynamic Pricing Programs in the MISO States in 2013

State	TOU	CPP	RTP
IA	X	X	X
IL	X		X
IN	X	X	X
KY	X		X
MI	X	X	X
MN	X	X	
MO	X		
MT	X		
ND	X	X	
NE	X	X	
OH	X	X	X
SD	X		
WI	X	X	X

Appendix Table 2. 2: Validity of the Instruments for the Retail Market Model

	Retail IV
Hansen-Sargan (1982) statistic	0.852
	(0.356)
Partial F-stat (1st stage)	89.02
	(0.0001)
Cragg-Donald Wald	184.842
	(19.93 (10% maximal IV size[17]))
	(11.59 (15% maximal IV size))
	(8.75 (20% maximal IV size))

P-values in parenthesis

Appendix Table 2. 3: Validity of the Instruments for the Wholesale Market Model

	Wholesale IV
Hansen-Sargan (1982) statistic	0.025
	(0.8747)
Partial F-stat (1st stage)	34.86
	(0.0001)
Cragg-Donald Wald	176.528
	(19.93 (10% maximal IV size))
	(11.59 (15% maximal IV size))
	(8.75 (20% maximal IV size))

P-values in parenthesis

[17] Maximal IV size represents the tolerable bias level based on the two-stage IV estimation. Partial F-statistic and Cragg-Donald statistics should be greater than the tolerable bias levels in order to reject the null hypothesis of endogenous regressors are unidentified.

Appendix Table 2. 4: Results from Industrial Demand: OLS and IV Estimations

	OLS	IV-1	IV-2
log_real_IndPrice	-0.089	-0.109	-0.169
	(-1.04)	(-1.05)	(-1.52)
L.lnindsalespercustomer	0.922***	0.548***	0.574***
	(24.23)	(3.56)	(3.81)
log_ManEmployment	0.086**	-0.592*	-0.656**
	(2.03)	(-1.87)	(-2.05)
log_real_ng	0.017	0.140	0.156
	(0.12)	(1.07)	(1.14)
log_sLMPPIA	-0.022**	-0.019**	
	(-2.36)	(-2.33)	
log_tempreture	-0.024	0.190	0.208
	(-0.06)	(0.24)	(0.25)
inter_iowa	-0.027	-0.162	-0.140
	(-0.67)	(-1.65)	(-1.49)
inter_illinois	-0.028	-0.127	-0.113
	(-0.56)	(-0.74)	(-0.65)
inter_indiana	-0.048	-0.130	-0.107
	(-0.95)	(-1.21)	(-0.98)
inter_kentucky	-0.050	-0.165*	-0.066
	(-0.61)	(-1.75)	(-0.55)
inter_michigan	-0.086**	-0.314**	-0.332**
	(-2.12)	(-2.35)	(-2.52)
inter_minnesota	-0.055	-0.247*	-0.225*
	(-1.26)	(-1.91)	(-1.75)
inter_montana	-0.124	0.032	
	(-1.63)	(0.34)	
inter_missouri	-0.118*	-0.190**	-0.176**
	(-1.85)	(-2.09)	(-2.07)
inter_n_dakota	0.012	-0.108	-0.087
	(0.17)	(-1.22)	(-0.93)
inter_nebraska	-0.146	-0.102	-0.071
	(-1.62)	(-0.94)	(-0.67)
inter_ohio	-0.065	-0.186	-0.170
	(-1.25)	(-1.64)	(-1.52)
inter_s_dakota	-0.007	-0.052	-0.023
	(-0.11)	(-0.55)	(-0.24)
dum_2001	0.110*	0.240***	0.239***
	(1.88)	(3.30)	(3.29)
dum_2002	0.130***	0.266***	0.255***
	(3.20)	(3.70)	(3.65)
dum_2003	-0.073	0.011	-0.003
	(-0.79)	(0.15)	(-0.04)
dum_2005	0.110	0.050	0.048
	(1.32)	(0.86)	(0.83)
dum_2007	0.079**	0.075*	0.073*
	(2.06)	(1.89)	(1.81)
dum_2008	0.175**	0.152*	0.159*
	(2.16)	(1.97)	(1.69)
dum_2009	0.141	0.090	0.119
	(1.25)	(0.85)	(0.94)
dum_2010	0.256***	0.157**	0.196**

	(3.89)	(2.33)	(2.28)
dum_2011	0.129***	0.091*	0.094
	(3.13)	(1.68)	(1.60)
dum_2012	0.058	0.056	0.072
	(1.07)	(0.70)	(0.86)
log_sLMAPIA			-0.019*
			(-1.67)
Constant	0.417		
	(0.28)		
R-sq	0.974	0.638	0.637

t statistics in parentheses * p<0.1 ** p<0.05 *** p<0.01

Appendix Table 2. 5: Peak Demand Events in MISO 2008 and 2013

Day	Month	Year	Hour
27	6	2013	15:00
18	7	2013	16:00
29	8	2013	16:00
10	9	2013	16:00
28	6	2012	17:00
23	7	2012	16:00
3	8	2012	16:00
12	1	2012	19:00
4	9	2012	17:00
7	6	2011	17:00
20	7	2011	17:00
2	8	2011	16:00
1	9	2011	16:00
6	12	2011	19:00
22	6	2010	17:00
13	12	2010	19:00
23	7	2010	16:00
10	8	2010	16:00
1	9	2010	16:00
25	6	2009	15:00
10	7	2009	16:00
10	8	2009	15:00
14	9	2009	16:00
15	1	2009	20:00
10	12	2009	19:00
26	6	2008	15:00
29	7	2008	17:00
1	8	2008	16:00
2	9	2008	16:00
24	1	2008	20:00

Source: Midcontinent Independent System Operator (MISO) Market Reports Archive

Appendix Table 2. 6: First Stage Regression Results

log_real_IndPrice	Coef.	Robust Std. Err.	t	P>t	[95% Conf.	Interval]
L1.lnindsalespercustomer	0.064562	0.02342	2.76	0.007	0.018159	0.110965
log_ManEmployment	-0.73702	0.122642	-6.01	0.000	-0.98002	-0.49402
log_real_ng	0.220892	0.055542	3.98	0.000	0.110842	0.330942
log_sLMAPIA	-0.01549	0.005173	-3	0.003	-0.02574	-0.00524
log_tempreture	0.831637	0.423829	1.96	0.052	-0.00813	1.671401
inter_iowa	0.125632	0.05201	2.42	0.017	0.022581	0.228683
inter_illinois	0.110147	0.052145	2.11	0.037	0.006828	0.213465
inter_indiana	0.118647	0.052303	2.27	0.025	0.015016	0.222278
inter_kentucky	0.24229	0.062493	3.88	0.000	0.118469	0.366112
inter_michigan	0.049773	0.060166	0.83	0.41	-0.06944	0.168985
inter_minnesota	0.161626	0.047441	3.41	0.001	0.067628	0.255624
inter_missouri	0.045117	0.05215	0.87	0.389	-0.05821	0.148446
inter_n_dakota	-0.03788	0.072349	-0.52	0.602	-0.18123	0.105471
inter_nebraska	0.156556	0.049639	3.15	0.002	0.058202	0.25491
inter_ohio	0.109199	0.049004	2.23	0.028	0.012103	0.206294
inter_s_dakota	0.166372	0.049725	3.35	0.001	0.067849	0.264895
dum_2001	0.335161	0.038195	8.77	0.000	0.259482	0.41084
dum_2002	0.584028	0.046583	12.54	0.000	0.491729	0.676327
dum_2003	0.052637	0.034715	1.52	0.132	-0.01615	0.121421
dum_2005	-0.06976	0.017756	-3.93	0.000	-0.10494	-0.03458
dum_2007	0.086922	0.023647	3.68	0.000	0.040067	0.133776
dum_2008	0.254025	0.041714	6.09	0.000	0.171374	0.336676
dum_2009	0.647829	0.06454	10.04	0.000	0.519951	0.775708
dum_2010	-0.18347	0.066188	-2.77	0.007	-0.31462	-0.05233
dum_2011	-0.36642	0.045008	-8.14	0.000	-0.45559	-0.27724
dum_2012	-0.07702	0.039926	-1.93	0.056	-0.15613	0.002091
log_GDPNOutil	1.021441	0.123741	8.25	0.000	0.776265	1.266618
L1.log_real_IndPrice	0.545597	0.057891	9.42	0.000	0.430894	0.6603

Appendix Table 2. 7: Real-Time Market Estimations for MISO

	All Day	On-Peak (8am-22pm)	On-Peak (3pm-8pm)	Off-Peak	DR Event
lnMISOSystem	-0.131***	-0.294***	-0.207***	-0.082*	-0.101***
	(-8.97)	(-10.54)	(-6.36)	(-1.92)	(-5.09)
L.lnactualloadmwh	0.973***				
	(497.62)				
TG	-0.002*	-0.002	-0.002		-0.006***
	(-1.66)	(-1.46)	(-0.87)		(-3.09)
LWY	-0.001	-0.006***	-0.005**		0.001
	(-0.95)	(-4.28)	(-2.55)		(0.42)
trend	-0.000	0.000	0.000	0.000	-0.000
	(-0.62)	(0.06)	(0.36)	(0.52)	(-1.12)
Pricesq	0.020***	0.040***	0.029***	0.011**	0.019***
	(9.73)	(10.87)	(6.83)	(2.14)	(5.56)
hourpeak	0.033***			0.035***	
	(40.99)			(7.59)	
interMAXtemp	-0.000***	-0.000***	-0.000**		
	(-3.02)	(-4.62)	(-2.29)		
interMINtemp	-0.000***	-0.000***			-0.000***
	(-4.46)	(-3.91)			(-5.10)
PEAKinter	-0.000***	-0.000***	-0.000***	-0.000	
	(-5.51)	(-5.60)	(-3.86)	(-1.28)	
hour2	0.026***			0.019***	0.031***
	(29.52)			(3.81)	(50.36)
hour3	0.037***			0.033***	0.044***
	(38.87)			(6.94)	(63.58)
hour4	0.052***			0.051***	0.060***
	(59.76)			(10.08)	(87.86)
hour5	0.076***			0.082***	0.082***
	(81.61)			(15.85)	(111.66)
hour6	0.107***			0.117***	0.108***
	(97.61)			(19.66)	(112.08)
hour7	0.125***			0.136***	0.121***
	(123.63)			(25.95)	(115.95)
hour8	0.086***	0.088***		0.105***	
	(121.41)	(74.02)		(19.78)	
hour9	0.067***	0.071***		0.091***	
	(98.66)	(65.75)		(16.43)	
hour10	0.055***	0.060***		0.084***	
	(80.13)	(56.66)		(13.77)	
hour11	0.048***	0.054***		0.078***	
	(74.93)	(51.38)		(14.13)	
hour12	0.041***	0.047***		0.073***	
	(66.97)	(45.11)		(14.55)	
hour13	0.036***	0.041***		0.064***	
	(61.75)	(41.46)		(13.08)	
hour14	0.033***	0.038***		0.056***	
	(59.06)	(38.78)		(12.29)	
hour15	0.029***	0.032***	-0.007***	0.049***	
	(52.02)	(31.66)	(-9.28)	(11.86)	
hour16	0.029***	0.031***	-0.007***	0.041***	
	(54.22)	(33.86)	(-10.16)	(9.47)	
hour17	0.033***	0.036***	-0.002***	0.039***	
	(63.36)	(39.62)	(-3.73)	(10.33)	
hour18	0.041***	0.046***	0.006***	0.039***	
	(58.90)	(38.32)	(8.30)	(7.14)	

hour19	0.044***	0.049***	0.009***	0.030***	
	(58.63)	(43.66)	(12.68)	(5.17)	
hour20	0.034***	0.040***		0.021***	
	(51.14)	(36.87)		(4.91)	
hour21	0.024***	0.028***		0.021***	
	(41.13)	(30.16)		(5.79)	
hour23	0.007***				0.003***
	(8.77)				(4.63)
jan	-0.001*	0.010***	0.010***		0.001
	(-1.75)	(15.24)	(10.37)		(1.55)
feb	0.004***	0.001**	0.018***		0.006***
	(7.17)	(1.99)	(17.33)		(7.24)
mar	-0.005***				0.006***
	(-9.93)				(5.37)
apr	-0.001**	-0.007***	0.002**		0.013***
	(-2.20)	(-11.11)	(2.32)		(11.95)
jun	-0.002***	-0.005***	-0.002*		0.000
	(-3.66)	(-6.27)	(-1.73)		(0.18)
jul	-0.001	0.001*			-0.004***
	(-1.12)	(1.82)			(-4.90)
sep	-0.002***	-0.001			-0.000
	(-2.79)	(-1.48)			(-0.39)
oct	-0.002***	-0.006***	0.005***		0.006***
	(-3.71)	(-6.70)	(4.67)		(6.27)
summer	0.005***	0.011***	0.002*		
	(7.47)	(14.05)	(1.89)		
winter	0.006***	-0.006***	0.011***		0.005***
	(9.64)	(-8.88)	(10.37)		(6.44)
fall	0.002***	0.000	0.007***		0.009***
	(3.92)	(0.23)	(6.57)		(11.53)
laglnactualloadmwh		0.978***	0.973***	0.971***	0.992***
		(272.11)	(220.71)	(60.20)	(335.83)
DRevent		0.007***	-0.001		
		(4.95)	(-0.31)		
dec		0.013***	0.013***		
		(19.02)	(12.99)		
aug			0.002**		
			(2.01)		
nov			0.010***		
			(10.56)		
may					0.007***
					(6.00)
hour24				-0.008*	
				(-1.68)	
Constant	0.441***	0.734***	0.645***	0.405***	0.145***
	(24.51)	(26.87)	(19.27)	(2.86)	(2.82)
N	48994	32353	13021	660	16641
R-sq	0.979	0.969	0.979	0.992	0.971
t statistics in parentheses					
="* p<0.1	** p<0.05	*** p<0.01"			

Appendix Table 3. 1: NEM Grade Calculation

Policy Metric	Description	Highest Points	Lowest Points
Individual System Capacity	Largest system allowed to net metering	+5 points for 2MW+	-1 Only residential below 20kW
Total Program Capacity Limits	Total Program Limit as percentage of peak demand	+2.5 or greater, no limit	-0.5 for less than 0.2%
Restrictions on Rollover	Rollover provisions	+1.5 for indefinite rollover at retail rate	-4 for no rollover permitted, excess energy donated to utility monthly
Metering Issues	Metering Provisions	+2 for no meter change requirements-customer-sited generator uses existing meter	-1 for Fixed TOU rate disadvantages small generators
REC	Renewable Energy Credit Ownership	+1 for Owned by customer	-5 for Transferred to utility without appropriate incentive
Eligible technologies	Eligible technologies	+1 for Solar, wind and other renewable zero-emission tech.	0 for excess solar and wind
Eligible Customers	Customer class eligibility	+2 for no eligible class restrictions	0 for residential only
Bonus for Aggregate Net Metering	Bonus	+1 for *A customer may aggregate all meters on his or her contiguous property for purposes of net metering*	
Bonus for Community Renewables	Bonus	+1 for *A customer may receive net metering credits for investing in or subscribing to a renewable energy system that may not be physically located on their property.*	
Safe Harbor Provisions, standby charges or other fees	Fee treatment	+3 for *Safe harbor language protects customers from unspecified additional equipment, fees, requirements to change tariffs, etc.*	-5 for per kWh fee on all production in addition to other fees
Policy Coverage	Utilities Covered	+1 for Rules apply to all utilities	0 for rules apply to investor-owned utilities only
Third-Party Model	Third Party PPA	+1 Presumed allowed net meter	-1 Presumed not allowed net meter
Source: Freeing the Grid: Best Practices in State Net Metering Policies and Interconnection Procedures 2010			

A: Full retail credit with no subtractions. Customers protected from fees and additional charges. Rules actively encourage use of DG.
B: Generally good net metering policies with full retail credit, but there could be certain fees or costs that detract from full retail equivalent value. There may be some obstacles to net metering
C: Adequate net metering rules, but there could be some significant fees or other obstacles that undercut the value or make the process of net metering more difficult.
D: Poor net metering policies with substantial charges or other hindrances. Many customers will forgo an opportunity to install DG because net metering rules subtract economic value.
F: Net metering policies that deter customer-sited DG
N/A: No state wide policy exist

Appendix Table 3. 2: Literature Review on Price Elasticity of Electricity Demand

Study by	Elasticity Range: Residential/Commercial	Estimation Method/Identification Method
Houthakker et al. (1974); Taylor (1975); Bohi and Zimmerman (1984); Dubin and MacFadden (1984)	-[0.2-0.7]	Simultaneous Equation Model, OLS
Maddala et al. (1997) Bernstein and Griffin (2006)	-[0.16-0.32]	OLS
Fell, Li and Paul (2010); Filippini (2011)	-[-.82-1.02] -[0.7-2.3](on-off peak)	GMM
Labendeira (2010)	-[0.069-0.2]	Tobit
Halvorsen (1975)	-[1.00-1.21]	Cost of fuel, average annual sales per customer, percentage of generation produced by publicly owned utilities, cost of labor
Wilder and Wilenborg (1975)	-[0.15-0.59]	2SLS as part of the system of 4 equations
Hausman, Kinnucan and MacFadden (1979)	-[0.13-0.22]	Demand weighted average price (they worked out the equation)
Fabrizio, Rose, Wolfram (2007)	No price elasticity of demand estimation	Modeled generator efficiency: used electricity demand as an instrument on the plant output.
Reiss and White (2005);	-[0.85-1.02]	Temperature, Degree Day, Cooling Degree Day, gross state product(GSP)
Alberini and Filippini (2011) These guys claim that not adding lagged price cause under estimation in the price elasticity demand for residential sector	-[0.56-1.03]	Lagged electricity price;
Alberini and Filippini (2011)	-[0.13-0.7]	Fixed effects, Random effects and GMM using IV as Lagged electricity price

Appendix Table 3. 3: State Policy Matrix for Residential Rooftop

	Un-restructured States		Restructured States	
NEM Grade	**2008**	**2012**	**2008**	**2012**
A	CO, FL	AZ, CA, CO, VT, WV	MD, NJ, PA	CT, DE, MA, MD, NJ, NY, OH, PA
B	KY, LA, VT, WY, CA, AZ	FL, HI, IA, IN, KS, KY, LA, NE, WA, WY	CT, DE, IL, MA, NY, OH, OR, RI	IL, ME, MI, NH, OR, RI
C	HI, IA, MN, MO	AK, MN, MO, WI		
D	ND, OK, WA, WI	NC, ND		
F	GA, IN, NC, WV	GA, OK, SC	TX	TX
N/A	AK, KS, NE, SC, SD	SD	MD, NJ, PA	CT, DE, MA, MD, NJ, NY, OH, PA

Appendix Table 3. 4: Data Sources for Regression Analysis

Variable	**Source**
Monthly Residential PV Capacity Installations	Energy Information Administration (EIA) 923 Monthly Reports
Monthly Utility Electricity Sales to Residential Sector	Energy Information Administration (EIA) 826 Monthly Electricity Reports
Monthly Residential Electricity and Natural Gas Price	Energy Information Administration (EIA) 826 Monthly Electricity Reports
Cost of PV	OpenPV Project by National Renewable Energy Laboratory (NREL)
Solar Radiation	National Renewable Energy Laboratory (NREL) Solar Radiation Database
State Regulatory Status	Energy Information Administration (EIA)
Net Energy Metering Grade	Solar Energy Industries Associations
ACEEE Score	American Counsel for an Energy Efficient Economy (ACEEE) State Energy Efficiency Scorecard
Temperature	Midwest Regional Climate Center
Disposable Income	Bureau of Economic Analysis